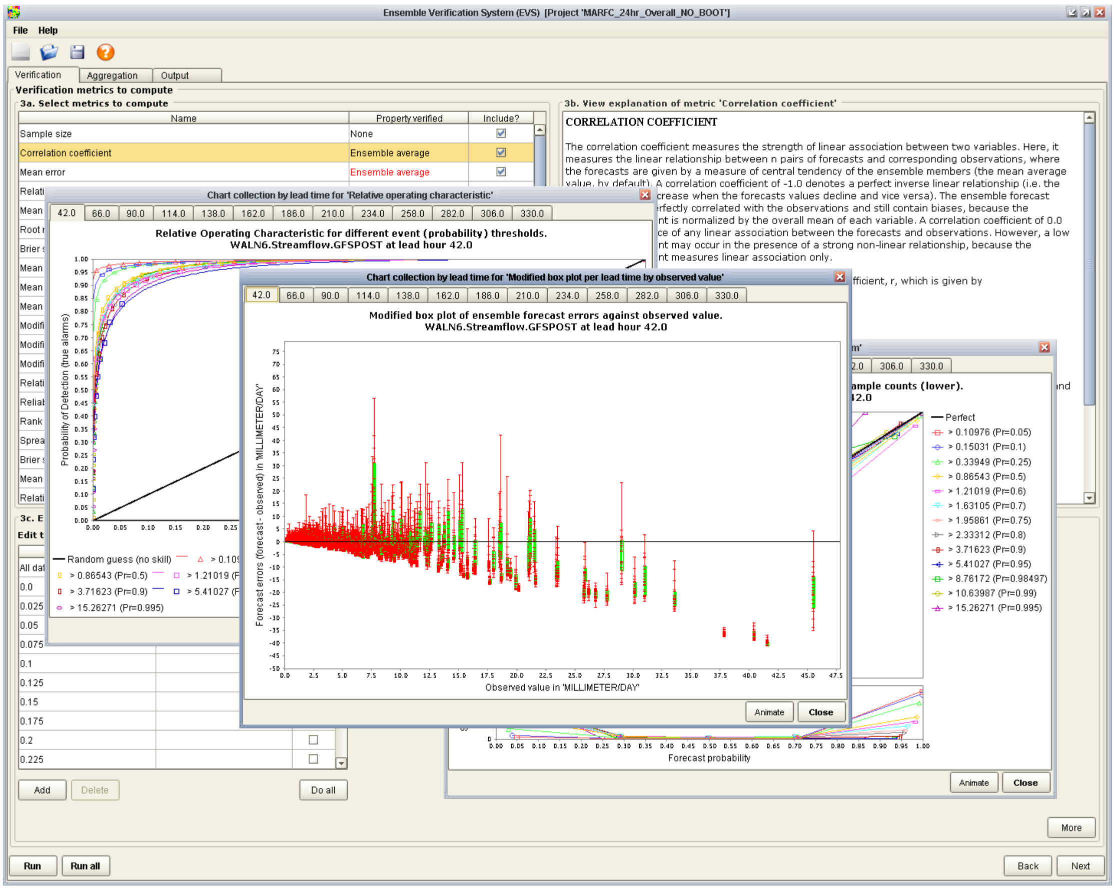
Ensemble Verification Service (EVS)

Version 5.5



Ensemble Verification System (EVS) [Project 'MARFC_24hr_Overall_NO_BOOT']
File
Help
Verification
Aggregation
Output
Verification metrics to compute
3a. Select metrics to compute
Name
Property verified
Include?
Sample size
None
Correlation coefficient
Ensemble average
Mean error
Ensemble average
3b. View explanation of metric 'Correlation coefficient'
Chart collection by lead time for 'Relative operating characteristic'
42.0
66.0
90.0
114.0
138.0
162.0
186.0
210.0
234.0
258.0
282.0
306.0
330.0
Relative Operating Characteristic for different event (probability) thresholds.
WALN6.Streamflow.GFSPOST at lead hour 42.0
Probability of Detection (true alarms)
Random guess (no skill)
> 0.86543 (Pr=0.5)
> 3.71623 (Pr=0.9)
> 15.26271 (Pr=0.995)
> 1.21019
> 5.41027
Chart collection by lead time for 'Modified box plot per lead time by observed value'
Modified box plot of ensemble forecast errors against observed value.
WALN6.Streamflow.GFSPOST at lead hour 42.0
Forecast errors (forecast - observed) in 'MILLIMETER/DAY'
Observed value in 'MILLIMETER/DAY'
ample counts (lower).
Perfect
> 0.10976 (Pr=0.05)
> 0.15031 (Pr=0.1)
> 0.33949 (Pr=0.25)
> 0.86543 (Pr=0.5)
> 1.21019 (Pr=0.6)
> 1.63105 (Pr=0.7)
> 1.95861 (Pr=0.75)
> 2.33312 (Pr=0.8)
> 3.71623 (Pr=0.9)
> 5.41027 (Pr=0.95)
> 8.76172 (Pr=0.98497)
> 10.63987 (Pr=0.99)
> 15.26271 (Pr=0.995)
Forecast probability
Animate
Close
Add
Delete
Do all
More
Run
Run all
Back
Next

CORRELATION COEFFICIENT

The correlation coefficient measures the strength of linear association between two variables. Here, it measures the linear relationship between n pairs of forecasts and corresponding observations, where the forecasts are given by a measure of central tendency of the ensemble members (the mean average value, by default). A correlation coefficient of -1.0 denotes a perfect inverse linear relationship (i.e. the crease when the forecasts values decline and vice versa). The ensemble forecast erfectly correlated with the observations and still contain biases, because the nt is normalized by the overall mean of each variable. A correlation coefficient of 0.0 ce of any linear association between the forecasts and observations. However, a low nt may occur in the presence of a strong non-linear relationship, because the nt measures linear association only.

fficient, r, which is given by

User’s Manual

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Preface

The Ensemble Verification Service (EVS) is a Java-based software tool originally developed by the U.S. National Weather Service's Office of Hydrologic Development (OHD) and, subsequently, by Hydrologic Solutions Limited (HSL), Southampton, UK. The software is currently developed and marketed by HSL as the Ensemble Verification System. The EVS is designed to verify ensemble forecasts of hydrologic and hydrometeorological variables, such as temperature, precipitation, streamflow and river stage. The software is intended to be flexible, modular, and open to accommodate enhancements and additions, not only by its developers, but also by its users. The EVS is "open source" software and is released under the GNU Lesser General Public License (LGPL), Version 3.0. We welcome your participation in the continuing development of the EVS toward a versatile and standardized tool for ensemble verification.

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Acknowledgments

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Disclaimer

This software and related documentation was originally developed by the National Weather Service (NWS) and, subsequently, by Hydrologic Solutions Limited (HSL), hereafter referred to as “The Developers.” Pursuant to title 17, section 105 of the United States Code this software is not subject to copyright protection and may be used, copied, modified, and distributed without fee or cost. Parties who develop software incorporating predominantly NWS developed software must include notice, as required by Title 17, Section 403 of the United States Code. The Developers provide no warranty, expressed or implied, as to the correctness of the furnished software or its suitability for any purpose. The Developers assume no responsibility, whatsoever, for its use by other parties, about its quality, reliability, or any other characteristic. The Developers may change this software to meet their own needs or discontinue its use without prior notice. The Developers cannot assist users without prior agreement and are not obligated to fix reported problems. The EVS is released under the GNU Lesser General Public License (LGPL) Version 3.0. A copy of the LGPL is provided with this distribution.

Contents

1. INTRODUCTION 5

2. INSTALLATION INSTRUCTIONS AND START-UP 8

2.1 Contents of the full distribution 8

2.2 Requirements 8

2.3 Unpacking and running the EVS 9

2.4 Troubleshooting the installation 10

2.5 Altering memory settings 11

2.6 Source code and documentation 11

2.7 Computer resource considerations 12

3. OVERVIEW OF FUNCTIONALITY 14

3.1 Summary of functionality in the EVS Version 5.5 14

3.2 Planned functionality 16

4. GETTING STARTED 17

4.1 Structure of the GUI 17

4.2 Stage 1: Verification 18

4.3 Stage 2: Aggregation 22

4.4 Stage 3: Output 23

4.5 File data formats supported by the EVS 24

4.6 Command line options 28

4.7 Changing the format of the XML outputs from the EVS 29

4.8 Creating custom plots of the EVS outputs in R 30

5. A DETAILED GUIDE TO THE OPTIONS IN EACH WINDOW OF THE GUI 31

5.1 Administrative functions in the main window 31

5.2 The first window in the Verification stage 31

5.3 The second window in the Verification stage 45

5.4 The Aggregation window 54

5.5 The Output window 57

6. THE VERIFICATION METRICS AVAILABLE IN THE EVS 62

6.1 Classes of verification metric and attributes of forecast quality 62

6.2 Metrics developed for the EVS with an emphasis on operational forecasting 66

7. EXAMPLE APPLICATIONS OF THE EVS 71

7.1 Precipitation forecasts from the NWS Ensemble Pre-Processor (EPP) 71

7.2 Streamflow forecasts from the NWS Ensemble Streamflow Prediction system 76

8. THE APPLICATION PROGRAMMERS INTERFACE (API) 82

8.1 Overview 82

8.2 Procedure for adding a new metric to the EVS 84

APPENDIX A1 VERIFICATION STATISTICS COMPUTED IN THE EVS 86

APPENDIX A2 XML OUTPUT FORMATS 103

APPENDIX A3 REFERENCES 117

1. INTRODUCTION

Ensemble forecasting is widely used in meteorology and, increasingly, in hydrology to quantify and propagate modeling uncertainty (Stensrud et al., 1999; Brown and Heuvelink, 2007; Park and Xu, 2009). Uncertainties in model predictions originate from the inputs, structure and parameters of a model, among other things (Brown and Heuvelink, 2005; Gupta et al., 2005). In practice, ensemble forecasts cannot account for all of these uncertainties, and some uncertainties are difficult to quantify accurately (NRC, 2006). Thus, ensemble forecasts are subject to errors. These errors are manifest as differences between the forecast probabilities and the corresponding observed probabilities over a large sample of forecasts and verifying observations (subject to sampling and observational uncertainty; Jolliffe and Stephenson, 2003; Hashino et al., 2006; Wilks, 2006). Unlike single-valued forecasts, ensemble forecasts cannot be verified with deterministic measures, such as the mean error or the root mean square error (RMSE). Rather, each ensemble member, and thus each error, is associated with only a partial probability of occurrence. Many of the techniques used to verify ensemble forecasts were pioneered in meteorology (Wilks, 2006). For example, the Brier Score (BS; Brier, 1950) was developed to verify probability forecasts of discrete weather events, such as tornados. The BS measures the average squared difference between the forecast probability of an event and its observed probability (which is 1 if the event occurred and 0 otherwise). With the growth of probabilistic forecasting, ensemble verification is increasingly used in other disciplines, such as hydrology (Bradley et al., 2004), oceanography (Park and Xu, 2009), ecology (Araújo and New, 2007) and volcanology (Bonadonna et al., 2005).

The basic attributes of ensemble forecast quality are broadly applicable, since they are concerned with probability distributions or measures on probability distributions. However, the specific approach to verification will depend on the forecast variables and their temporal and spatial scales, as well as the intended applications and users of the forecasts (e.g. research versus operational forecasting). In order to support ensemble verification for a wide range of applications in hydrology and beyond, flexible and user-friendly software is required. This is illustrated with an example from the National Weather Service (NWS). The River Forecast Centers (RFCs) of the NWS produce ensemble forecasts of temperature, precipitation and streamflow at a variety of lead times (Schaake et al., 2007; Demargne et al., 2007; Demargne et al., 2009, Wu et al., 2010). In one experimental operation, ensemble traces of precipitation and temperature are generated from single-valued forecasts using an

Ensemble Pre-Processor (EPP; Schaake et al., 2007, Wu et al., 2010). These traces are input into the Ensemble Streamflow Prediction (ESP) subsystem of the NWS River Forecast System (NWSRFS; NWS, 2005), from which ensemble traces of streamflow are output. There is a need to verify these forecasts and to identify the factors responsible for model error and skill in different situations. Verification is required at multiple temporal and spatial scales, ranging from minutes and kilometers (e.g. for flash flood guidance) to years and entire regions (e.g. for water resource planning and national verification). Furthermore, there is a need to support both operational forecasting within the RFCs and hydrologic research and development within the NWS. In order to meet these needs, work on ensemble verification is separated into two themes (see Demargne et al., 2009 for further details); 1) verification and bias-correction of real-time ensemble forecasts, which should *directly* improve decisions that rely on forecast probabilities ("real-time verification"; see Brown and Seo, 2010a); and 2) verification of archived operational forecasts and hindcasts, which should *indirectly* improve decision making via enhanced techniques for generating ensemble forecasts ("diagnostic verification").

The Ensemble Verification Service (EVS) is a flexible, user-friendly, software tool that is designed to verify ensemble forecasts of continuous numeric variables, such as temperature, precipitation and streamflow (Brown et al., 2010b). The EVS can be applied to forecasts from any number of geographic locations (points or areas) and issued with any frequency and lead time. It can also aggregate forecasts in time, such as daily precipitation totals based on hourly forecasts, and can aggregate verification statistics across several discrete locations. However, it does not support the verification of uncertain spatial fields, such as gridded atmospheric pressure, or uncertain spatial objects, such as storm cells.

A verification study with the EVS is separated into three stages (Brown et al., 2010b), namely: 1) Verification; 2) Aggregation; and 3) Output. In the Verification stage, one or more Verification Units (VUs) are defined. Each VU comprises a set of forecasts and verifying observations for one environmental variable at one geographic location. The ensemble forecasts and observations are provided in an XML or ASCII format. The Verification stage also requires one or more verification metrics to be selected. The forecasts and observations are then paired by forecast lead time and the verification metrics computed. The results are written to the Output dialog, where the metrics can be plotted in an internal viewer or written to file in a variety of graphical formats or in XML. The Aggregation stage allows for the averaging of verification statistics across multiple VUs.

The verification metrics in the EVS comprise both deterministic metrics, which verify the ensemble mean forecast, and probabilistic metrics, which verify the forecast probabilities. The probabilistic metrics comprise distribution-oriented metrics, which verify the joint probability distribution of the forecasts and observations (or its factors), and measure-oriented statistics, which summarize the forecast quality in a score. Their combination allow for specific attributes of forecast quality, such as reliability and discrimination, to be examined in varying levels of detail. This is important, as the EVS is intended for a wide range of applications and users, including both scientific researchers and operational forecasters in the National Weather Service (NWS). In addition to implementing standard measures of forecast quality, the EVS provides a platform for testing new verification metrics.

The EVS is currently being used by operational forecasters at several of the NWS RFCs. It is also used routinely to support scientific research and development within the NWS (e.g. Demargne et al., 2007; Wu et al., 2010; Brown et al., 2010b). In future, the EVS will be expanded to allow for the verification of both single-valued and probabilistic forecasts issued by the RFCs. Such verification is needed to identify the nature and sources of forecasting error, document forecast performance as a function of changing practices, and to support targeted improvements in forecast models and field data collection. These topics are being pursued by the NWS in collaboration with Environment Canada, the European Center for Medium Range Weather Forecasting (ECMWF), the Verification Testbed of the Hydrologic Ensemble Prediction Experiment (HEPEX), and with several universities. It is hoped that the introduction of verification standards, supported by a common verification tool, will allow for inter-comparisons of forecasting models and methods in different regions and over extended periods of time, contributing to the better use of uncertain weather and water forecasts, as outlined in NRC (2006).

The EVS is free to use, distribute, and modify, but is provided without technical support.

2. INSTALLATION INSTRUCTIONS AND START-UP

2.1 Contents of the full distribution

The full distribution comprises (** are required to run the EVS):

Item	Description
EVS.jar**	The main executable and associated libraries
EVS_MANUAL.pdf	This manual
EVS_RELEASE_NOTES.pdf	The release notes, including changes and bug-fixes
EVS_TEST_DATA.zip	An example dataset for running the EVS (**see README.TXT**)
/reporting	Contains a template to report bugs or suggested enhancements
EVS_SOURCE.zip	A directory containing the Java source-code for the EVS
/javadoc	A directory containing “Javadoc” source code documentation
/nonsrc/rscripts/	A series of scripts for generating custom verification plots in R
/nonsrc/statsexplained/	Html guides to particular metrics available in the EVS.
EVS.bat	Example Windows batch file and command to use more RAM
EVS.ico	An icon to use when associating EVS project files with the EVS

2.2 Requirements

No formal installation of the EVS is required. However, in order to run the EVS you will need:

1. The Java^{TM} Runtime Environment (JRE) version 7.0 (1.7) or higher. You can check your current version of Java by opening a command prompt and typing java –version. If the command is not recognized, you do not have a version of the JRE installed. If the installed version is older than 1.7, you should update the JRE. The JRE is free software and may be downloaded from the Sun website:

   http://java.sun.com/javase/downloads/index.jsp

2. The EVS executable, `EVS.jar`, and associated resources in `EVS_5.5.zip`;

3. Microsoft Windows (98/2000/NT/XP/Vista/7) or Linux Operating System (OS). In addition, you will need:
   - A minimum of 256MB of Random-Access Memory (RAM) and ~50MB of hard-disk space free (not including the associated datasets).
   - For many applications of the EVS, involving verification of large datasets more RAM and disk space will be required. A minimum of 1GB of RAM and 2GB of disk space is recommended (see Section 2.7).

2.3 Unpacking and running the EVS

Once you have obtained the EVS software, unpack the zipped archive to any directory of your computer (e.g. `C:/Program Files/EVS_5.5/`) using, for example, WinZip^{TM} on Windows or the `unzip` command in Linux/Unix:

```
unzip EVS_5.5.zip
```

There are two possible ways of running the EVS, namely: 1) by executing the Graphical User Interface (GUI); and 2) by executing the EVS from the command line with a pre-defined project file.

Executing the EVS with the GUI:

Once you have unpacked the software, you may run the EVS by double-clicking on “EVS.jar” in Windows or by opening a command prompt, navigating to the root directory, and typing a java command that references the EVS jar file, such as:

```
java -jar EVS.jar.
```

The GUI can be opened with a specified EVS project file by typing:

```
java -jar EVS.jar –gui project_1.evs
```

where `project_1.evs` is an EVS project file (the file need not be located in the root directory, but should be referenced by its full path otherwise). Project files can be associated with the EVS application in Windows and other OS. In Windows, this is achieved by updating the registry to associate .evs project files with a batch file that contains the following command:

```
java -jar EVS.jar -gui %1
```

where `%1` is substituted for an EVS project file on execution (e.g. on double-clicking an EVS project file) and `EVS.jar` is the full path to the EVS executable. An EVS icon is provided in the root directory of the EVS distribution, namely EVS.ico.

Executing the EVS without the GUI:

In order to execute the EVS without the GUI, you must have one or more pre-defined EVS projects available. The EVS projects are specified in XML (see Appendix A2) and may be created with or without the GUI. For example, a base project may be created with the GUI and then altered manually or with a script outside of the GUI (e.g. changing the input and output data sources). One or more EVS projects may be invoked from a command prompt by typing a java command with the paths to the project(s) listed afterwards, for example:

```
java -jar EVS.jar project_1.evs
```

where `project_1.evs` is an EVS project file. By default, the graphical and numerical results are written to the output directories specified in the projects.

2.4 Troubleshooting the installation

List of typical problems and actions:

– **"Nothing happens when executing EVS.jar"**

Ensure that the Java Runtime Environment (JRE) is installed on your machine and is in your PATH. The JRE should be version 7.0 (1.7) or higher. To check that a suitable version of the JRE is installed and in your PATH, open a command prompt and type:

```
java -version
```

If the command is not recognized, the JRE is not installed and in your PATH. If the version is below 7.0 (1.7), update the JRE (see above).

If this does not help, check the root directory of your installation for a log file named `evs.log`. Send the error message to the authors for advice on how to proceed (evs@hydrosolved.com).

– **"An error message is thrown when executing EVS.jar"**

If an error message is thrown by the JRE (i.e. a java error appears in the message), the error may be caused by the local installation of Java.

2.5 Altering memory settings

By default, the amount of RAM memory available to the EVS is restricted by the Java Virtual Machine. In order to perform ensemble verification with large datasets, it may be necessary to change this default and increase the amount of memory available. This is achieved by executing the EVS on the command line, whether invoking the GUI or running a project without the GUI. To execute the GUI with altered memory settings, navigate to the installation directory of the EVS, and type:

```
java -Xmx1000m -jar EVS.jar
```

where **`1000`** is the maximum amount of memory (in megabytes) allocated to the EVS in this example. The maximum memory allocation should be significantly lower than the total amount of RAM available on your machine, as other programs, including the OS, will require memory to run. For example, on a 32-bit Windows OS with 4000 megabtyes of memory, around 1200 megabytes of memory will typically be available for the EVS. The EVS will only start with an increased memory setting if the Java Virtual Machine can actually allocate the desired amount of memory.

2.6 Source code and documentation

The Java source code for the EVS can be found in the src.zip archive in the root directory of your installation. The Application Programming Interface (API) is described in the html documentation, which accompanies the software (in the `/javadoc` directory).

2.7 Computer resource considerations

The time required to execute an EVS project, as well as the amount of RAM and hard-disk space required, will depend on a wide range of factors, including:

- The number of forecast locations;
- The number of paired forecasts and observations for each location, which itself depends on the forecast frequency, the forecast horizon or number of "lead times", the number of ensemble members etc;
- The verification metrics required and the number of thresholds at which they are computed;
- Whether the forecasts and observations are already paired (quicker) or need to be paired and written to an associated paired file (slower);
- When performing conditional verification (i.e. with a subset of the overall pairs), whether those pairs should also be written to file (slower, and the default) or not written (quicker);
- When writing the pairs, whether they are written in a compressed (gzip) format (considerably less space) or in uncompressed ASCII format (easier to check);
- When aggregating verification results across several locations, whether the verification metrics should be computed by averaging the values of the verification metrics at the individual locations (quicker, and the default) or by pooling the pairs and then computing the metrics for the pooled pairs (much slower);
- The requirements for computing confidence intervals via bootstrap resampling, including the number and types of metrics for which confidence intervals are required and the number of samples requested. When several processors/cores are directly available to the EVS, the bootstrap samples will be distributed across the available processors/cores (the bootstrap algorithm is multi-threaded); and
- Whether the EVS is executed from the command line or via the GUI (in terms of RAM consumed). When executing from the command line, each VU and AU is executed sequentially and the numerical and/or graphical outputs are written sequentially. When executing from the GUI, all of the verification results (not the

verification pairs, unless pooling pairs with aggregation) are stored in memory, until a decision is made about what outputs to generate.

- The computer resources available, including the amount of RAM allocated. If the EVS application becomes progressively slower while reading forecasts, this may originate from "housekeeping" activities; that is, an attempt to free memory within the constraints imposed. In that case, increase the memory available on startup (see Section 2.5).

All floating point numbers stored and manipulated by the EVS are double-precision (64-bit) numbers. Thus, a single observed or forecast (ensemble member) value will consume 8 bytes of RAM. The EVS requires more RAM than implied by the data, as some duplication of data is necessary, and the EVS itself has an overhead of ~15 megabytes. In the absence of sufficient memory to complete a calculation, an `OutOfMemoryError` will be thrown. To save disk space, the default maximum precision for writing floating point numbers (the forecasts and observations) to the EVS paired file is *five* decimal places, with fewer decimal places written as required. The maximum precision may be controlled via the GUI (see Section 4) or directly via the `<paired_write_precision>` tag within the EVS project file (see Appendix A2, but note that calculations are always performed in double-precision).

3. OVERVIEW OF FUNCTIONALITY

3.1 Summary of functionality in the EVS Version 5.5

A complete list of the enhancements, changes in default behavior, and bug fixes between successive versions of the EVS can be found in the release notes that accompany this distribution (`EVS_RELEASE_NOTES.pdf`).

The functionality currently supported by the EVS includes:

- Pairing of observed and ensemble forecast values, which may be provided in a variety of file formats, to perform verification for a given forecast point or area. The observed and forecast values may be in different time systems or at different temporal scales, the times and scales being defined by the user;

- Computation of multiple verification metrics for arbitrary numeric forecast variables (e.g. precipitation, temperature, streamflow, river stage) at a single forecast point or area. The verification metrics are computed for each of the forecast lead times available. The available metrics include:
  - For verification of the ensemble average forecast (mean, median, mode):
    - the correlation coefficient;
    - the mean error,
    - the root mean square error;
    - the mean absolute error; and
    - the relative mean error (the mean error as a fraction of the mean observation).
  - For verification of the ensemble-derived forecast probabilities:
    - the Brier Score, including its calibration-refinement factors (“reliability”, “resolution” and “uncertainty”) and likelihood-base-rate factors (“Type-II conditional bias”, “discrimination” and “sharpness”);
    - the Brier Skill Score and its calibration-refinement and likelihood-base-rate factors;
    - the Continuous Ranked Probability Score and its calibration-refinement factors;
    - the Continuous Ranked Probability Skill Score and its calibration-refinement factors;

  - the Relative Operating Characteristic, including the fitting of a smooth curve (bivariate normal model);
  - the Relative Operating Characteristic Score, including the integration of a fitted curve (bivariate normal model);
  - the reliability diagram;
  - the rank histogram; and
  - several newly-developed metrics (see Section 6.2).

- Conditional verification. Two forms of conditional verification are supported by the EVS, namely 1) the identification of logical "pre-conditions" to sub-select pairs; and 2) verification with respect to thresholds (for metrics that verify discrete events, such as flooding, these thresholds are necessary, as they define the events). The pre-conditions include: 1) a restricted set of dates (e.g. months, days, weeks, hours of the day, or some combination of these); 2) a restricted set of observed or forecast values (e.g. ensemble mean exceeding some threshold, maximum observed values within a 90 day window, forecast probability of exceeding some threshold greater than 0.95, observed values of another variable not exceeding some threshold). When verifying the remaining pairs against particular thresholds, the thresholds may be defined with respect to the climatological probability distribution (based on a specified sample of observed data), such as the 95th percentile flow, or in real values, such as flood stage;

- Aggregation of verification results across a group of forecast locations, either by averaging the (possibly weighted) verification metrics from the individual locations or by pooling the pairs and computing the verification metrics for the pooled pairs. When aggregating in space, the individual locations must have common properties (e.g. common variables, units and scales); and

- Generation of graphical and numerical products, which may be written to file in various formats (e.g. png, jpeg, svg files) or plotted within EVS. In addition, several R scripts are provided in the `/nonsrc/rscripts` directory for importing and plotting data in the R statistical environment (R Development Core Team, 2008).

- The ability to compute verification results for each of *m* bootstrap re-samples of the (possibly conditional) verification pairs and to generate associated measures of sampling uncertainty, such as one or more confidence intervals (of which one can be displayed for each metric). The bootstrap resampling procedure can account for space-time dependence in the verification pairs across multiple lead times and locations and the computational load is distributed across the available processing cores.

3.2 Planned functionality

The additional functionalities planned for future versions of the EVS includes, in no particular order:

- The addition of options for combining several metrics into one plot and for increasing the flexibility of plotting more generally;

- Functionality for verifying joint distributions; that is, the statistical dependencies in space and time, as well as the marginal distributions (e.g. to verify the reliability of the correlations associated with forecast values across several lead times);

- The ability to compute forecast skill for several reference forecasts at once, such as climatology, persistence or raw model output (e.g. before data assimilation or manual adjustment). Currently, only one reference forecast may be defined for each combination of forecast point and skill score;

- The development of a batch language to support the generation of verification products without running the GUI. For example, it should be possible to create a template point and apply this to a wider group of forecast points, changing only the observed and forecast data sources via a batch processor;

- The ability to separate errors in hydrologic forecasts into phase (timing) and amplitude errors; and

- The ability to verify additional types of forecasts, such as probability forecasts and single-valued forecasts.

4. GETTING STARTED

As indicated above, there are two possible ways to use the EVS, namely: 1) with the Graphical User Interface (GUI); and 2) from the command line with a pre-defined project. The GUI provides a structured interface for defining an ensemble verification study and is considered in some detail below. Once familiar with the software, or when conducting verification at a large number of forecast points, execution via the command line, with a pre-defined project, may be preferred.

4.1 Structure of the GUI

A verification study with the EVS is separated into three stages:

1. **Verification:** identification of one or more Verification Units (VUs), pairing of forecasts and observations, and computation of verification metrics. Each VU comprises a set of forecasts and verifying observations for one environmental variable at one geographic location, together with a list of verification metrics to be computed;

2. **Aggregation:** identification of one or more Aggregation Units (AUs). Each aggregation unit comprises two or more VUs and is used to measure the average performance across these VUs. This is an optional stage;

3. **Output:** production of graphical and numerical outputs of the verification statistics for one or more previously defined VUs and AUs.

These stages are separated into "tabbed panes" in the GUI, which also contains a taskbar for administrative operations, such as creating, opening, and saving projects (Fig. 1). Initially, a verification study may involve linearly navigating through these tabbed panes until one or more VUs and AUs have been defined, the verification statistics generated, and the results written to file. However, once a VU has been defined and saved, the point of entry into the software may vary. For example, an existing project may be modified, a new AU identified from a set of pre-existing VUs, or new graphical outputs generated. Project files, which are written in an XML format (see Section 4.4 for the file data formats), can be created or edited manually and then executed from a command prompt (e.g. Microsoft DOS, Cygwin, Linux) rather than from the GUI, thereby allowing simple batch processing of VUs and AUs through shell scripting.

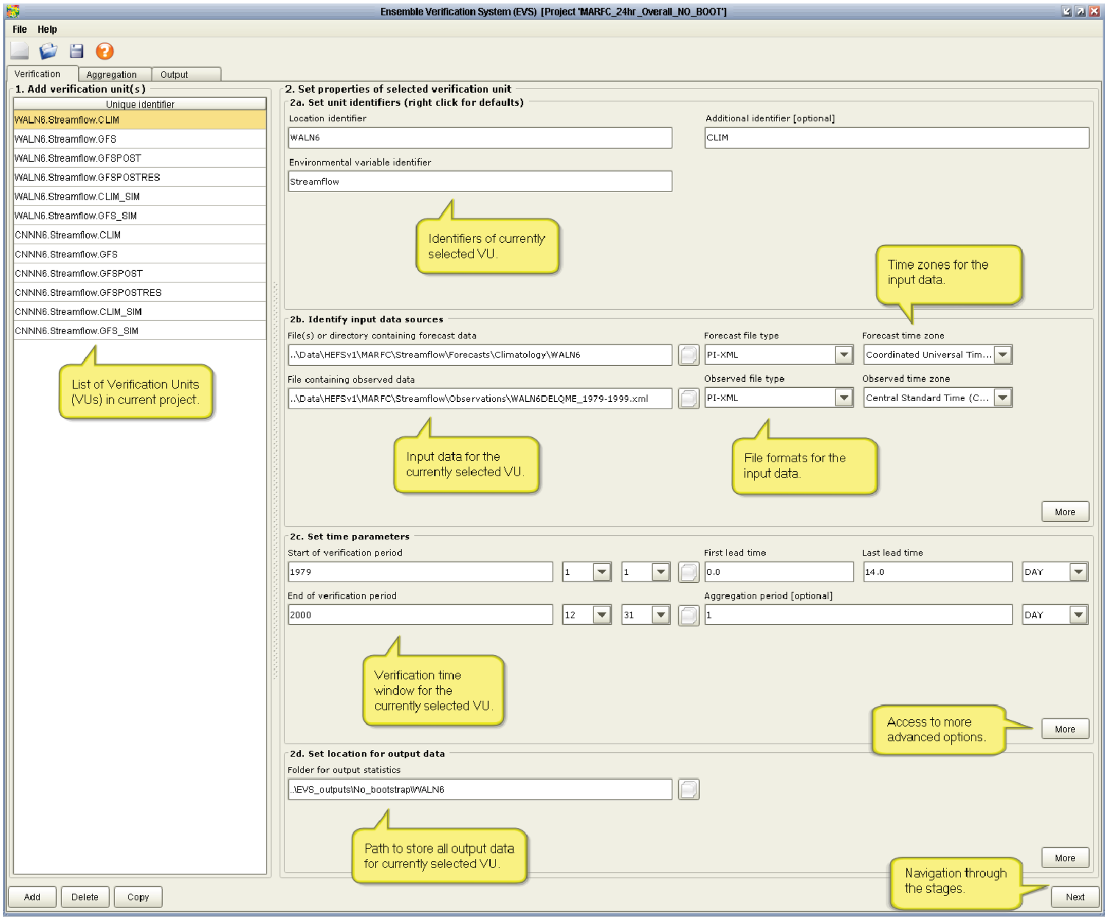
Each tabbed pane within the GUI comprises one or more panels, which correspond to intermediate steps within the verification stage, such as the specification of data sources (one panel in Stage 1) and the selection of verification statistics to compute (another panel in Stage 1). At each stage, “basic options”, such as the identification of observed and forecast data, are separated from more “advanced options”, such as the selection of specific months over which to verify the forecasts. The latter are accessible via pop-up dialogs.

4.2 Stage 1: Verification

The first stage of a verification study in the EVS involves the identification of a VU, followed by the selection and computation of verification metrics (Fig. 1). The basic attributes of a VU are:

- a unique identifier, which is built from a ‘location identifier’, an ‘environmental variable identifier’ and, optionally, an ‘additional identifier’, which can be used to distinguish between forecasts from several modeling systems, among other things;
- the paths to the observed and forecast data, which may be absolute or relative to the directory in which the EVS.jar is located;
- the file formats in which the forecasts and observations are stored (Section 4.5)
- the time systems in which the forecasts and observations are stored (e.g. UTC);
- the temporal and spatial ‘support’ of the forecasts and observations (i.e. space-time scale) and their associated measurement units;
- the period for which verification statistics should be computed;
- the forecast lead times for which verification statistics should be computed; and
- the location where verification outputs should be written, which may be an absolute path or relative to the directory in which the EVS.jar is located.

Fig. 1: The opening panel in the "Verification" stage



Ensemble Verification System (EVS) [Project 'MARFC_24hr_Overall_NO_BOOT']

1. Add verification unit(s)

Unique identifier
WALN6.Streamflow.CLIM
WALN6.Streamflow.GFS
WALN6.Streamflow.GFSPOST
WALN6.Streamflow.GFSPOSTRES
WALN6.Streamflow.CLIM_SIM
WALN6.Streamflow.GFS_SIM
CNNN6.Streamflow.CLIM
CNNN6.Streamflow.GFS
CNNN6.Streamflow.GFSPOST
CNNN6.Streamflow.GFSPOSTRES
CNNN6.Streamflow.CLIM_SIM
CNNN6.Streamflow.GFS_SIM

2. Set properties of selected verification unit

2a. Set unit identifiers (right click for defaults)

Location identifier: WALN6
Additional identifier [optional]: CLIM
Environmental variable identifier: Streamflow

2b. Identify input data sources

File(s) or directory containing forecast data: ..\Data\HEFSv1\MARFC\Streamflow\Forecasts\Climatology\WALN6
Forecast file type: PI-XML
Forecast time zone: Coordinated Universal Tim...
File containing observed data: ..\Data\HEFSv1\MARFC\Streamflow\Observations\WALN6DELQME_1979-1999.xml
Observed file type: PI-XML
Observed time zone: Central Standard Time (C...

2c. Set time parameters

Start of verification period: 1979 1 1
First lead time: 0.0
Last lead time: 14.0 DAY
End of verification period: 2000 12 31
Aggregation period [optional]: 1 DAY

2d. Set location for output data

Folder for output statistics: ..\EVS_outputs\No_bootstrap\WALN6

List of Verification Units (VUs) in current project.

Identifiers of currently selected VU.

Time zones for the input data.

Input data for the currently selected VU.

File formats for the input data.

Verification time window for the currently selected VU.

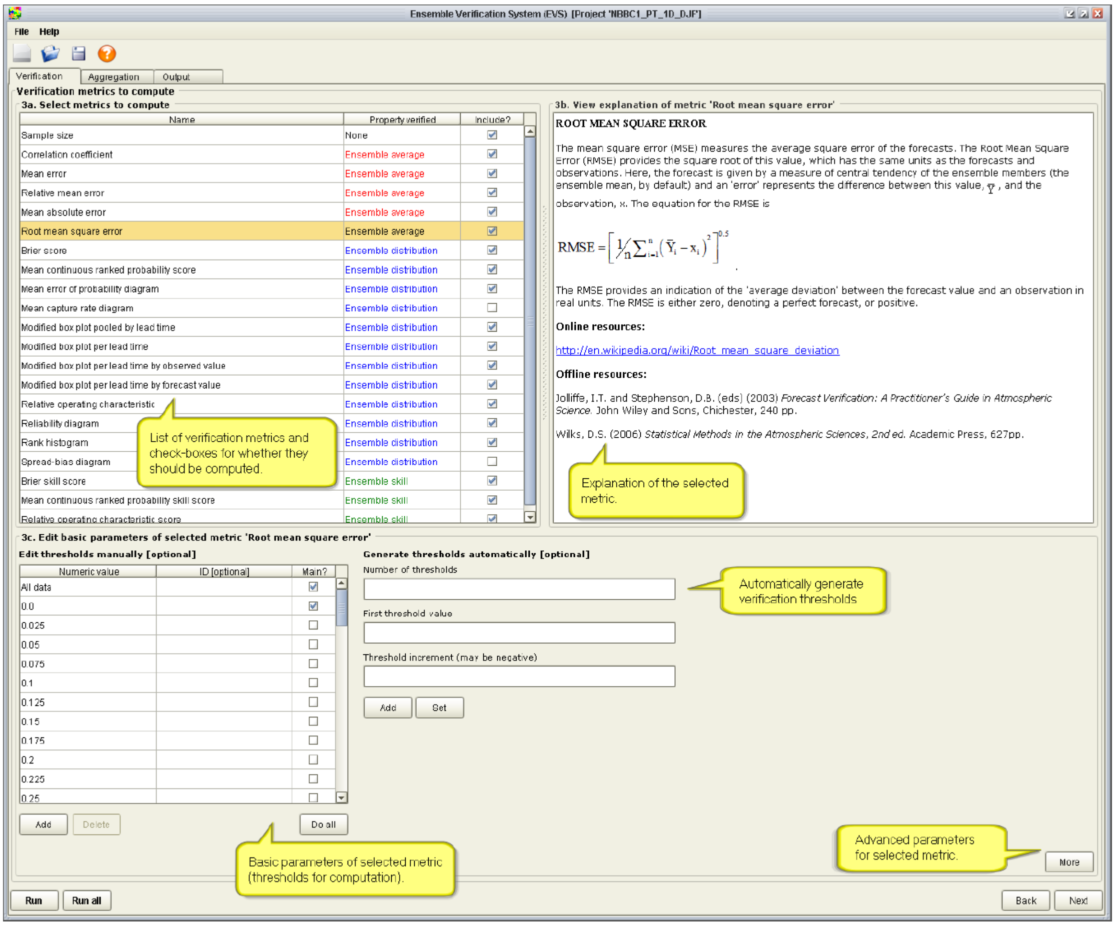
Access to more advanced options.

Path to store all output data for currently selected VU.

Navigation through the stages.

In addition to the basic attributes of a VU, several refinements are possible. For example, the verification period may be refined to include only winter months or specific days of the week. Similarly, the analysis may be restricted to a subset of the observed and forecast values, such as temperature forecasts whose ensemble mean is below freezing. Collectively, these "pre-conditions" lead to some of the pairs being ignored when computing the verification results. Another common requirement is to verify the forecasts at aggregated temporal scales. For example, six-hourly precipitation totals may be aggregated to daily totals before conducting verification. Temporal aggregation is achieved by applying an aggregation function (e.g. the sum) to each ensemble trace within the period of aggregation, and then collating the traces into an aggregated ensemble forecast. This ensures that any statistical dependencies between forecast lead times are preserved in the aggregated traces. Temporal disaggregation is not supported by the EVS.

Fig. 2: The second panel in the "Verification" stage


Ensemble Verification System (EVS) [Project 'NBBC1_PT_1D_DJF']
File
Help
Verification
Aggregation
Output
List of verification metrics and check-boxes for whether they should be computed.
Explanation of the selected metric.
Automatically generate verification thresholds
Basic parameters of selected metric (thresholds for computation).
Advanced parameters for selected metric.
Add
Delete
Do all
Add
Set
More
Run
Run all
Back
Next

Verification metrics to compute

3a. Select metrics to compute

Name	Property verified	Include?
Sample size	None	☑
Correlation coefficient	Ensemble average	☑
Mean error	Ensemble average	☑
Relative mean error	Ensemble average	☑
Mean absolute error	Ensemble average	☑
Root mean square error	Ensemble average	☑
Brier score	Ensemble distribution	☑
Mean continuous ranked probability score	Ensemble distribution	☑
Mean error of probability diagram	Ensemble distribution	☑
Mean capture rate diagram	Ensemble distribution	□
Modified box plot pooled by lead time	Ensemble distribution	☑
Modified box plot per lead time	Ensemble distribution	☑
Modified box plot per lead time by observed value	Ensemble distribution	☑
Modified box plot per lead time by forecast value	Ensemble distribution	☑
Relative operating characteristic	Ensemble distribution	☑
Reliability diagram	Ensemble distribution	☑
Rank histogram	Ensemble distribution	☑
Spread-bias diagram	Ensemble distribution	□
Brier skill score	Ensemble skill	☑
Mean continuous ranked probability skill score	Ensemble skill	☑
Relative operating characteristic score	Ensemble skill	☑

3b. View explanation of metric 'Root mean square error'

ROOT MEAN SQUARE ERROR

The mean square error (MSE) measures the average square error of the forecasts. The Root Mean Square Error (RMSE) provides the square root of this value, which has the same units as the forecasts and observations. Here, the forecast is given by a measure of central tendency of the ensemble members (the ensemble mean, by default) and an 'error' represents the difference between this value, $\bar{Y}$, and the observation, x. The equation for the RMSE is

$$\mathrm{RMSE} = \left[1/n \sum_{i=1}^{n} \left(\bar{Y}_i - x_i \right)^2 \right]^{0.5}$$

The RMSE provides an indication of the 'average deviation' between the forecast value and an observation in real units. The RMSE is either zero, denoting a perfect forecast, or positive.

Online resources:

http://en.wikipedia.org/wiki/Root_mean_square_deviation

Offline resources:

Jolliffe, I.T. and Stephenson, D.B. (eds) (2003) *Forecast Verification: A Practitioner's Guide in Atmospheric Science.* John Wiley and Sons, Chichester, 240 pp.

Wilks, D.S. (2006) *Statistical Methods in the Atmospheric Sciences, 2nd ed.* Academic Press, 627pp.

3c. Edit basic parameters of selected metric 'Root mean square error'

Edit thresholds manually [optional]

Numeric value	ID [optional]	Main?
All data		☑
0.0		☑
0.025		□
0.05		□
0.075		□
0.1		□
0.125		□
0.15		□
0.175		□
0.2		□
0.225		□
0.25		□

Generate thresholds automatically [optional]

Number of thresholds

First threshold value

Threshold increment (may be negative)

Once a VU has been defined, one or more verification metrics are selected from a tabular display for calculation (Fig. 2). The metrics are grouped into single-valued measures, which evaluate the quality of the ensemble average forecast (e.g. mean, median or mode), probabilistic metrics, which measure errors in the forecast probabilities, and skill scores, which measure the relative performance of two forecasting systems in terms of a given, probabilistic, metric. When selecting a particular metric (Fig. 2), a description of that metric, including links to further reading (online and offline), appear in the adjacent dialog (Fig. 2). Many of the probabilistic metrics are formulated for discrete events, such as the occurrence of precipitation or flooding, rather than the forecast probability distribution as a whole, which comprises an infinite number of possible events. Here, the forecast events are verified *after* applying any pre-conditions to remove pairs (see above). Thus, in designing a verification study, the identification of discrete events should be considered jointly with the specification of any pre-conditions to remove pairs (e.g. selecting particular months or verification pairs whose observation exceeds a threshold).

The metrics may be computed for several discrete events (conditions), for which the event thresholds and associated logical conditions must be defined (e.g. <, >). The event thresholds may be given in real units, such as flow in m^3 s^{-1}, or in observed climatological probabilities. Real units are useful when an event threshold is physically meaningful, such as the exceedence of a flood threshold. Climatological probabilities are useful when the aim is to verify the full range of forecast conditions or when the verification results will be averaged across several locations with different observed climatologies. However, the climatological probabilities are computed from a limited sample of observations and are, therefore, subject to sampling uncertainty. For convenience, the option to verify against thresholds is also provided for the deterministic metrics and for those probabilistic metrics that do not require discrete events. While these metrics depend continuously on the data, they may be computed for subsets of the overall dataset (selected by thresholds) in order to evaluate the ensemble forecast quality in a conditional sense. The thresholds may be input manually or generated semi-automatically using a combination of: 1) the number of thresholds; 2) the first threshold; and 3) a constant increment between thresholds, which may be positive (increasing from the first threshold) or negative (decreasing). Optionally, the thresholds identified for one metric can be applied to all other metrics for the selected VU (the “Do all” button in Fig. 2). The thresholds may be identified as “main” thresholds or “auxiliary” thresholds. Currently, this distinction affects plotting only; the verification results for “main” thresholds are plotted within the EVS and the results for both “main” and “auxiliary” thresholds are written to file, allowing more complex plots to be generated outside of the EVS (e.g. plots of verification scores as a “continuous” function of threshold value).

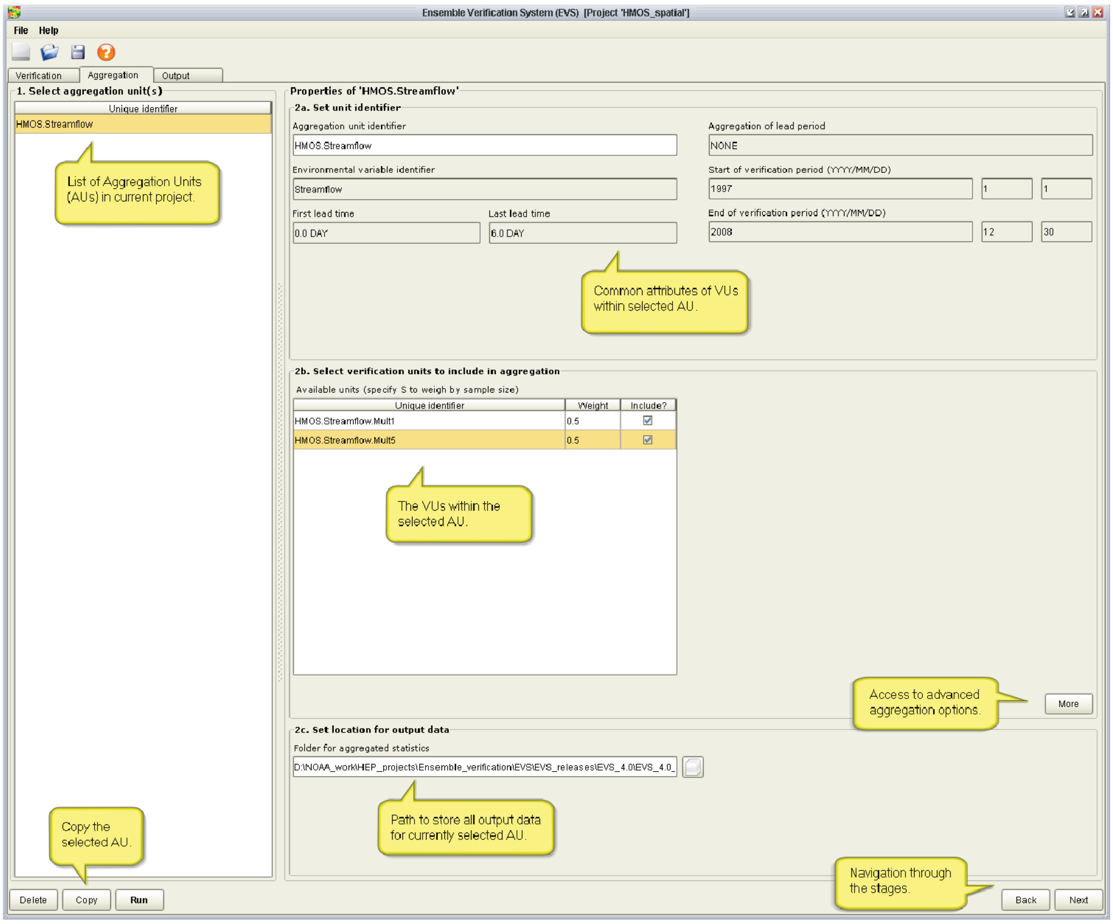
Depending on the chosen verification metric, other parameters may be modified (see Section 5.3 also). For example, the reliability of the forecast probabilities may be computed by grouping the forecast probabilities into smaller bins (with finer resolution, but fewer samples per bin) or larger bins (coarser resolution, but more samples per bin).

On executing a VU for the first time, the forecasts and observations are paired together by forecast valid time and lead time. Verification is conducted separately for each forecast lead time, as forecasting errors depend strongly on lead time. The paired data are then written to file (Section 4.5), both to enable quality control and to improve the speed of execution when modifying and re-running VUs. Since all of the outputs from the EVS are based on the paired data, they should be checked to ensure that the forecasts and observations were read and interpreted correctly (e.g. that the time systems were correctly specified).

4.3 Stage 2: Aggregation

In order to evaluate the aggregate performance of a forecasting system across a range of forecast locations, two or more VUs may be aggregated. This is conducted in the Aggregation panel of the EVS, where an Aggregation Unit (AU) is defined (Fig. 3). The potential AUs are determined automatically by the GUI upon adding or editing VUs. A potential AU is added to the Aggregation panel for each set of VUs that are completely defined and comparable. Two VUs are comparable if they share forecast variables with common temporal support (after temporal aggregation), common measurement units, and verification statistics with common parameter values, including common thresholds.

Fig. 3: The only panel in the "Aggregation" stage



Ensemble Verification System (EVS) [Project 'HMOS_spatial']

1. Select aggregation unit(s)

Unique identifier
HMOS.Streamflow

Properties of 'HMOS.Streamflow'

2a. Set unit identifier

Aggregation unit identifier: HMOS.Streamflow

Environmental variable identifier: Streamflow

First lead time: 0.0 DAY

Last lead time: 6.0 DAY

Aggregation of lead period: NONE

Start of verification period (YYYY/MM/DD): 1997 1 1

End of verification period (YYYY/MM/DD): 2008 12 30

2b. Select verification units to include in aggregation

Available units (specify S to weigh by sample size)

Unique identifier	Weight	Include?
HMOS.Streamflow.Mult1	0.5	☑
HMOS.Streamflow.Mult5	0.5	☑

2c. Set location for output data

Folder for aggregated statistics: D:\NOAA_work\HEP_projects\Ensemble_verification\EVS\EVS_releases\EVS_4.0\EVS_4.0_

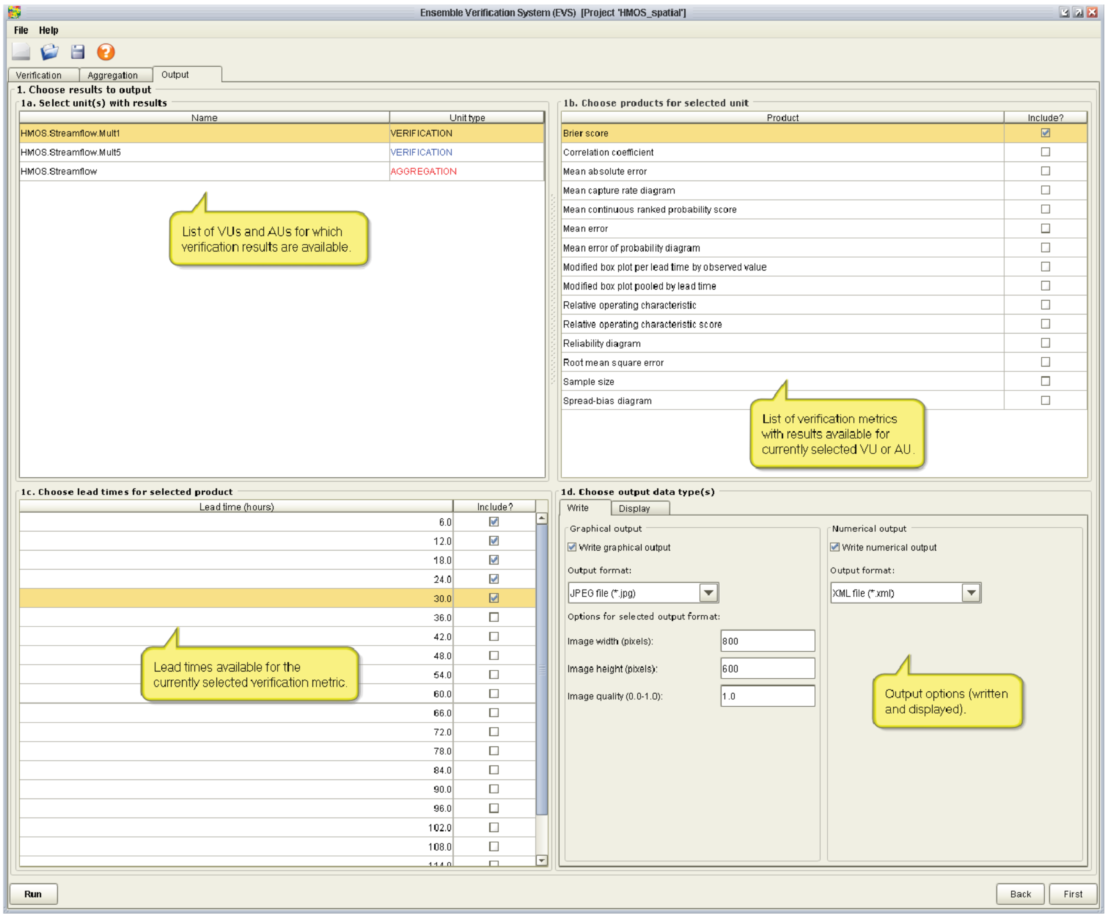
File
Help
Verification
Aggregation
Output
List of Aggregation Units (AUs) in current project.
Common attributes of VUs within selected AU.
The VUs within the selected AU.
Access to advanced aggregation options.
More
Path to store all output data for currently selected AU.
Copy the selected AU.
Navigation through the stages.
Delete
Copy
Run
Back
Next

By default, the verification results for an AU comprise a weighted average of the verification results from the component VUs. Optionally (under the advanced options accessed via the "**More**" button in Fig. 3), the verification metrics may be derived by pooled the pairs from several locations, rather than averaging the verification results (this is rarely feasible for large datasets). Once a potential AU has been determined in the GUI, four attributes are user-defined (Fig. 3): 1) a unique identifier for the AU; 2) the component VUs, which are selected from a list of candidates; 3) the weight associated with each VU in the aggregation (which is ignored when pooling pairs); and 4) the output directory for the aggregated statistics. On executing an AU, the verification metrics from the component VUs are collated and their weighted averages determined. For verification metrics that comprise binned statistics (e.g. the reliability diagram; see below), the sample means are computed for each bin in turn. For verification statistics that are conditional upon one or more event thresholds, the statistics are averaged across the same thresholds at each location. In order to have a meaningful spatial aggregation, the threshold must have a consistent physical interpretation in space and time, such as the exceedence of a local flood threshold rather than a fixed river stage. The weights assigned to each VU must be within [0,1] and the sum of all weights must be equal to 1. By default, equal weights are assigned to each VU, but unequal weights may be input manually or the character 'S' specified to weigh by the relative sample size at the first forecast lead time (maintaining constant weights across lead times).

4.4 Stage 3: Output

The Output panel of the EVS stores the verification results for each of the VUs and AUs in the current project. The results are organized by the unique identifier of the VU or AU, the name of the verification metric, and by forecast lead time (Fig. 4). The VUs and AUs available for plotting are shown in the top left table and are colored blue and red, respectively (Fig. 4). On selecting a particular VU or AU, a list of metrics with available results appears in the right-hand table. On selecting a particular metric, the bottom left table displays a list of lead times (in hours) for which the metric results are available. The basic options for plotting and writing metrics are shown in the bottom-right dialog. Options are provided on the tables for rapidly selecting particular combinations of metric and lead time. The options are provided in context menus, which are displayed by right-clicking on one of the tables. For example, by right-clicking on the table of metrics (top right in Fig. 4), an option appears for selecting all metrics and lead times. The metrics can be plotted in an internal graphing tool, which includes basic functionality for animating metrics across a sequence of lead times, or written to file in a variety of graphical formats (Section 4.4). Also, the underlying statistics can be written to file in an XML format and viewed in a text editor or web browser.

Fig. 4: The only panel in the “Output” stage



1. Choose results to output

1a. Select unit(s) with results

Name	Unit type
HMOS.Streamflow.Mult1	VERIFICATION
HMOS.Streamflow.Mult5	VERIFICATION
HMOS.Streamflow	AGGREGATION

List of VUs and AUs for which verification results are available.

1b. Choose products for selected unit

Product	Include?
Brier score	☑
Correlation coefficient	☐
Mean absolute error	☐
Mean capture rate diagram	☐
Mean continuous ranked probability score	☐
Mean error	☐
Mean error of probability diagram	☐
Modified box plot per lead time by observed value	☐
Modified box plot pooled by lead time	☐
Relative operating characteristic	☐
Relative operating characteristic score	☐
Reliability diagram	☐
Root mean square error	☐
Sample size	☐
Spread-bias diagram	☐

List of verification metrics with results available for currently selected VU or AU.

1c. Choose lead times for selected product

Lead time (hours)	Include?
6.0	☑
12.0	☑
18.0	☑
24.0	☑
30.0	☑
36.0	☐
42.0	☐
48.0	☐
54.0	☐
60.0	☐
66.0	☐
72.0	☐
78.0	☐
84.0	☐
90.0	☐
96.0	☐
102.0	☐
108.0	☐
114.0	☐

Lead times available for the currently selected verification metric.

1d. Choose output data type(s)

Write | Display

Graphical output

☑ Write graphical output

Output format: JPEG file (*.jpg)

Options for selected output format:

Image width (pixels): 800

Image height (pixels): 600

Image quality (0.0-1.0): 1.0

Numerical output

☑ Write numerical output

Output format: XML file (*.xml)

Output options (written and displayed).

4.5 File data formats supported by the EVS

The file data formats supported by the EVS are summarized in Table 1. Further details can be found in Appendix A2. They are separated into: 1) input data, comprising the ensemble forecasts and verifying observations for each VU; 2) paired data, comprising the paired forecasts and observations for a specific VU; 3) output data, comprising the verification statistics for a particular VU or AU in a graphical or numerical format; and 4) a project file, containing the parameter values of one or more VUs and AUs.

As indicated above, a VU is defined for each forecast variable and location. The input data for a single VU comprises the ensemble forecasts, which may be provided in one or multiple files, and the single-valued observations, which are provided in a single file.

Table 1: main file formats supported by the EVS

Data store	Format	Extension	Description
Project data	XML	evs	VUs and AUs and their parameters
Paired data	XML	xml	Paired forecasts and observations
Input data	ASCII	fcst	Ensemble forecasts in ASCII
	ASCII	obs	Observations in ASCII
	XML	xml	Ensemble forecasts in PI-XML
	XML	xml	Observations in PI-XML
	XML	fi/bin	Ensemble forecasts in binary Fast Infoset XML
	XML	fi/bin	Observations in binary Fast Infoset XML
	TAR/GZIP	tar.gz or tgz	Tarred and Gzipped ASCII or PI-XML forecasts
	NetCDF	nc	Ensemble forecasts in NetCDF [experimental]
	NetCDF	nc	Observations in NetCDF [experimental]
Graphical output	JPEG	jpg	Plots of verification metrics in raster format
	PNG	png	Plots of verification metrics in raster format
	SVG	svg	Plots of verification metrics in vector format
Numerical output	XML	xml	Numerical output of verification metrics

The forecasts and observations can be provided in XML or ASCII formats and the ASCII and PI-XML forecast files can be provided separately or inside a tarred and gzipped archive. Reading of NetCDF time-series files is supported experimentally, for which some information can be found here:

https://publicwiki.deltares.nl/display/NETCDF/Time+series

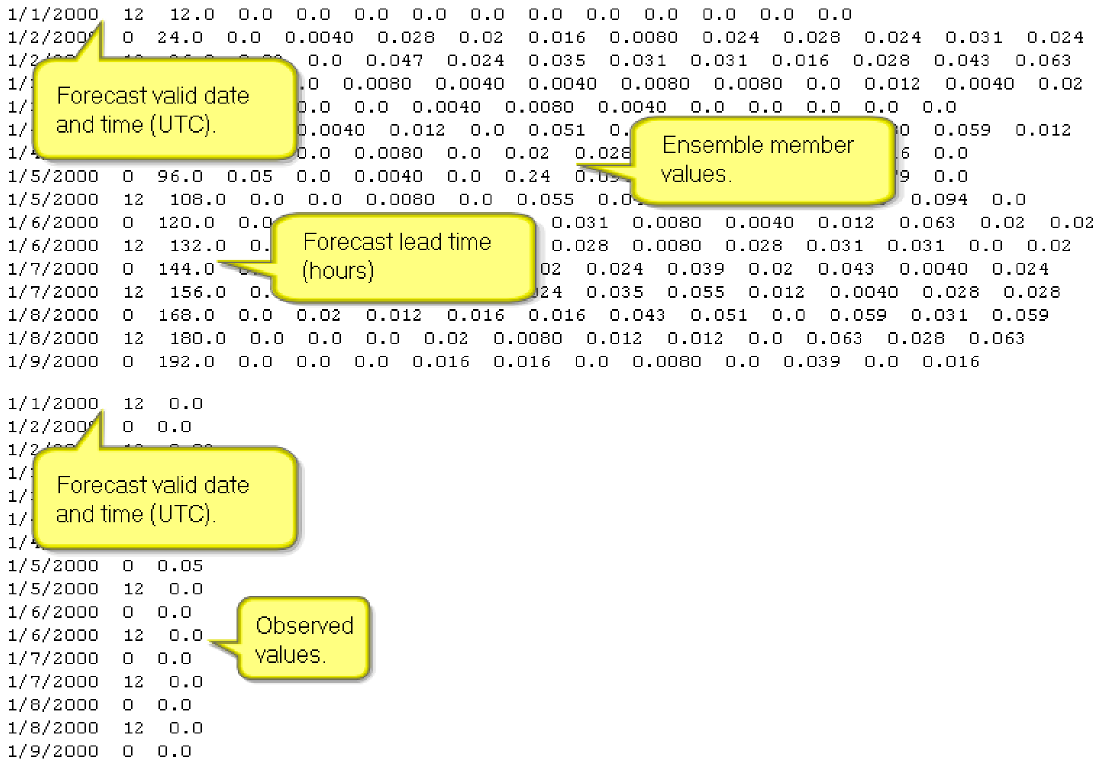
Various internal formats are used by the NWS for storing and exchanging ensemble forecasts and observations. These can also be read by the EVS, but are not described here. The ASCII format for storing the ensemble forecasts comprises one forecast per line (Fig. 5 shows sixteen forecasts). Each forecast requires the forecast valid date and time, the forecast lead time, and the forecast ensemble members *in* *trace-order* (this is important to preserve any temporal statistical dependencies when aggregating forecasts in time). The default format for dates and times is MM/dd/yyyy HH, but other formats can be defined manually (see Section 5.2). The forecast lead times are always given in hours. Adjacent entries are separated by whitespace or a comma. The ASCII format for storing the single-valued observations also comprises one instance per line, and includes the date and time of the observation, together with the observed value (Fig. 6). Again, adjacent entries can be separated by whitespace or a comma. The XML format for storing the observed and forecast data (as opposed to paired data: see below) follows the Published-Interface (PI-) XML format used in the Flood Early Warning System (FEWS). The XML format is described in detail here:

http://public.deltares.nl/display/FEWSDOC/The+Delft-Fews+Published+interface+(PI)

Several NWS formats are also supported by the EVS, including the "NWS Card format" and the "NWS CS binary" format. The NWS Card format is described here:

http://www.nws.noaa.gov/ohd/hrl/nwsrfs/users_manual/part7/_pdf/72datacard.pdf

Fig. 5: The ASCII format for ensemble forecasts (upper) and observations (lower)



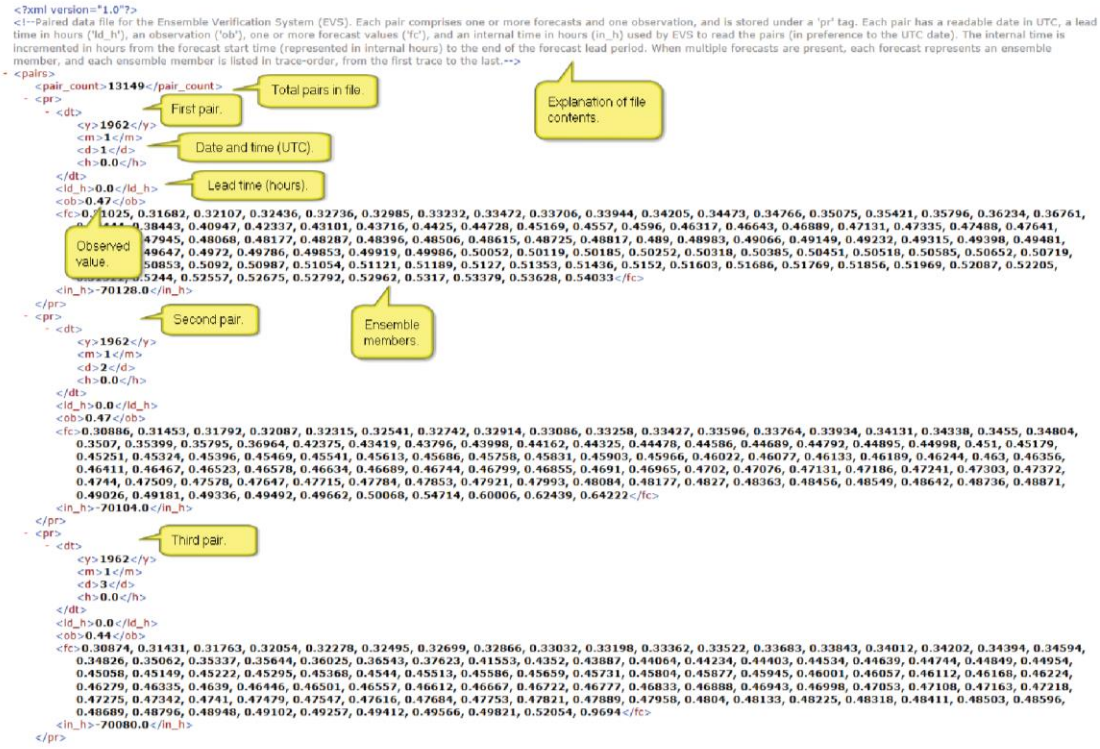
```
1/1/2000   12   12.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1/2/200    0   24.0   0.0   0.0040   0.028   0.02   0.016   0.0080   0.024   0.028   0.024   0.031   0.024
1/2                          0.0   0.047   0.024   0.035   0.031   0.031   0.016   0.028   0.043   0.063
1/                          .0   0.0080   0.0040   0.0040   0.0080   0.0080   0.0   0.012   0.0040   0.02
1/                          .0   0.0   0.0040   0.0080   0.0040   0.0   0.0   0.0   0.0   0.0
1/                          .0040   0.012   0.0   0.051   0.                        0   0.059   0.012
1/                          .0   0.0080   0.0   0.02   0.028                        6   0.0
1/5/2000   0   96.0   0.05   0.0   0.0040   0.0   0.24   0.0                        9   0.0
1/5/2000   12   108.0   0.0   0.0   0.0080   0.0   0.055   0.0                        0.094   0.0
1/6/2000   0   120.0   0.0                        0.031   0.0080   0.0040   0.012   0.063   0.02   0.02
1/6/2000   12   132.0   0.                        0.028   0.0080   0.028   0.031   0.031   0.0   0.02
1/7/2000   0   144.0                        02   0.024   0.039   0.02   0.043   0.0040   0.024
1/7/2000   12   156.0   0.                        24   0.035   0.055   0.012   0.0040   0.028   0.028
1/8/2000   0   168.0   0.0   0.02   0.012   0.016   0.016   0.043   0.051   0.0   0.059   0.031   0.059
1/8/2000   12   180.0   0.0   0.0   0.0   0.02   0.0080   0.012   0.012   0.0   0.063   0.028   0.063
1/9/2000   0   192.0   0.0   0.0   0.0   0.016   0.016   0.0   0.0080   0.0   0.039   0.0   0.016

1/1/2000   12   0.0
1/2/200    0   0.0
1/2
1/
1/
1/
1/
1/5/2000   0   0.05
1/5/2000   12   0.0
1/6/2000   0   0.0
1/6/2000   12   0.0
1/7/2000   0   0.0
1/7/2000   12   0.0
1/8/2000   0   0.0
1/8/2000   12   0.0
1/9/2000   0   0.0
```

Forecast valid date and time (UTC).
Ensemble member values.
Forecast lead time (hours)
Forecast valid date and time (UTC).
Observed values.

Once a VU has been executed in the EVS, the forecasts and observations are written to a paired file in an XML format. The paired file stores each ensemble forecast together with its verifying observation. Each pair contains the date and time in Coordinated Universal Time (UTC), the forecast lead time, the observed value and the ensemble members, in trace-order, separated by commas (Fig. 6). The pairs are organized by forecast valid time, from the earliest forecast to the latest, and by forecast lead time, from the shortest lead time to the longest. The decimal precision with which to write pairs can be controlled (see Section 5.2).

Fig. 6: The paired file format

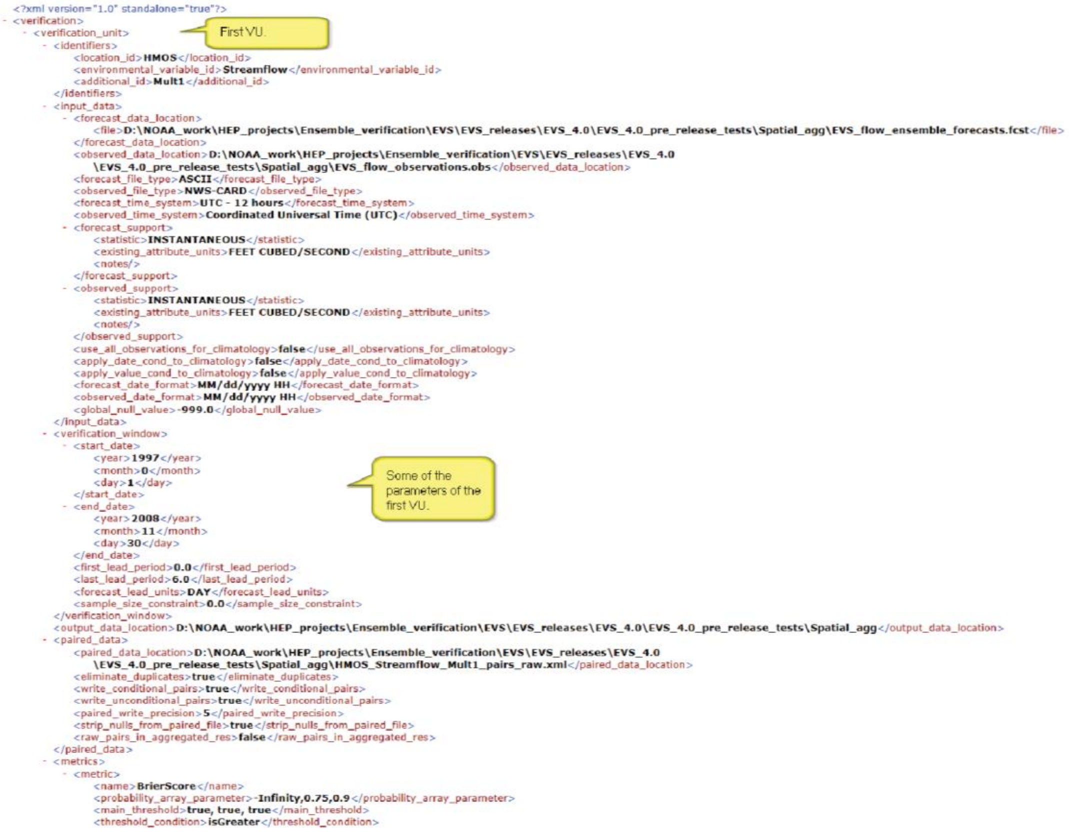


```
<?xml version="1.0"?>
<!--Paired data file for the Ensemble Verification System (EVS). Each pair comprises one or more forecasts and one observation, and is stored under a 'pr' tag. Each pair has a readable date in UTC, a lead
time in hours ('ld_h'), an observation ('ob'), one or more forecast values ('fc'), and an internal time in hours (in_h) used by EVS to read the pairs (in preference to the UTC date). The internal time is
incremented in hours from the forecast start time (represented in internal hours) to the end of the forecast lead period. When multiple forecasts are present, each forecast represents an ensemble
member, and each ensemble member is listed in trace-order, from the first trace to the last.-->
- <pairs>
    <pair_count>13149</pair_count>
  - <pr>
    - <dt>
        <y>1962</y>
        <m>1</m>
        <d>1</d>
        <h>0.0</h>
      </dt>
      <ld_h>0.0</ld_h>
      <ob>0.47</ob>
      <fc>0.[illegible]1025, 0.31682, 0.32107, 0.32436, 0.32736, 0.32985, 0.33232, 0.33472, 0.33706, 0.33944, 0.34205, 0.34473, 0.34766, 0.35075, 0.35421, 0.35796, 0.36234, 0.36761,
        0.[illegible].38443, 0.40947, 0.42337, 0.43101, 0.43716, 0.4425, 0.44728, 0.45169, 0.4557, 0.4596, 0.46317, 0.46643, 0.46889, 0.47131, 0.47335, 0.47488, 0.47641,
        [illegible]47945, 0.48068, 0.48177, 0.48287, 0.48396, 0.48506, 0.48615, 0.48725, 0.48817, 0.489, 0.48983, 0.49066, 0.49149, 0.49232, 0.49315, 0.49398, 0.49481,
        [illegible]49647, 0.4972, 0.49786, 0.49853, 0.49919, 0.49986, 0.50052, 0.50119, 0.50185, 0.50252, 0.50318, 0.50385, 0.50451, 0.50518, 0.50585, 0.50652, 0.50719,
        [illegible]50853, 0.5092, 0.50987, 0.51054, 0.51121, 0.51189, 0.5127, 0.51353, 0.51436, 0.5152, 0.51603, 0.51686, 0.51769, 0.51856, 0.51969, 0.52087, 0.52205,
        [illegible].5244, 0.52557, 0.52675, 0.52792, 0.52962, 0.5317, 0.53379, 0.53628, 0.54033</fc>
      <in_h>-70128.0</in_h>
    </pr>
  - <pr>
    - <dt>
        <y>1962</y>
        <m>1</m>
        <d>2</d>
        <h>0.0</h>
      </dt>
      <ld_h>0.0</ld_h>
      <ob>0.47</ob>
      <fc>0.30886, 0.31453, 0.31792, 0.32087, 0.32315, 0.32541, 0.32742, 0.32914, 0.33086, 0.33258, 0.33427, 0.33596, 0.33764, 0.33934, 0.34131, 0.34338, 0.3455, 0.34804,
        0.3507, 0.35399, 0.35795, 0.36964, 0.42375, 0.43419, 0.43796, 0.43998, 0.44162, 0.44325, 0.44478, 0.44586, 0.44689, 0.44792, 0.44895, 0.44998, 0.451, 0.45179,
        0.45251, 0.45324, 0.45396, 0.45469, 0.45541, 0.45613, 0.45686, 0.45758, 0.45831, 0.45903, 0.45966, 0.46022, 0.46077, 0.46133, 0.46189, 0.46244, 0.463, 0.46356,
        0.46411, 0.46467, 0.46523, 0.46578, 0.46634, 0.46689, 0.46744, 0.46799, 0.46855, 0.4691, 0.46965, 0.4702, 0.47076, 0.47131, 0.47186, 0.47241, 0.47303, 0.47372,
        0.4744, 0.47509, 0.47578, 0.47647, 0.47715, 0.47784, 0.47853, 0.47921, 0.47993, 0.48084, 0.48177, 0.4827, 0.48363, 0.48456, 0.48549, 0.48642, 0.48736, 0.48871,
        0.49026, 0.49181, 0.49336, 0.49492, 0.49662, 0.50068, 0.54714, 0.60006, 0.62439, 0.64222</fc>
      <in_h>-70104.0</in_h>
    </pr>
  - <pr>
    - <dt>
        <y>1962</y>
        <m>1</m>
        <d>3</d>
        <h>0.0</h>
      </dt>
      <ld_h>0.0</ld_h>
      <ob>0.44</ob>
      <fc>0.30874, 0.31431, 0.31763, 0.32054, 0.32278, 0.32495, 0.32699, 0.32866, 0.33032, 0.33198, 0.33362, 0.33522, 0.33683, 0.33843, 0.34012, 0.34202, 0.34394, 0.34594,
        0.34826, 0.35062, 0.35337, 0.35644, 0.36025, 0.36543, 0.37623, 0.41553, 0.4352, 0.43887, 0.44064, 0.44234, 0.44403, 0.44534, 0.44639, 0.44744, 0.44849, 0.44954,
        0.45058, 0.45149, 0.45222, 0.45295, 0.45368, 0.4544, 0.45513, 0.45586, 0.45659, 0.45731, 0.45804, 0.45877, 0.45945, 0.46001, 0.46057, 0.46112, 0.46168, 0.46224,
        0.46279, 0.46335, 0.4639, 0.46446, 0.46501, 0.46557, 0.46612, 0.46667, 0.46722, 0.46777, 0.46833, 0.46888, 0.46943, 0.46998, 0.47053, 0.47108, 0.47163, 0.47218,
        0.47275, 0.47342, 0.4741, 0.47479, 0.47547, 0.47616, 0.47684, 0.47753, 0.47821, 0.47889, 0.47958, 0.4804, 0.48133, 0.48225, 0.48318, 0.48411, 0.48503, 0.48596,
        0.48689, 0.48796, 0.48948, 0.49102, 0.49257, 0.49412, 0.49566, 0.49821, 0.52054, 0.9694</fc>
      <in_h>-70080.0</in_h>
    </pr>
```

The output files from the EVS comprise the verification statistics for a specific VU or AU in one of several graphical formats, and corresponding numerical results in an XML format (see Appendix A2). The supported graphical formats include two raster formats: the Portable Network Graphic (PNG) format (a lossless format) and the Joint Photographic Experts Group (JPEG) format (a lossy format). The Scalable Vector Graphics (SVG) format is also supported by the EVS, as this allows for verification plots to be rescaled without loss of quality. Scripts are also available to import and plot the numerical results in R (R Development Core Team, 2008), where many more output formats and plotting options are available. Example scripts are provided in the `nonsrc\rscripts` directory of the installation.

Finally, the parameters of each VU and AU are saved in a project file in an XML format. The project files are ordinarily written by the EVS, but may be produced or edited outside of the EVS (e.g. with a script, to enable batch processing). The XML is organized by VU and AU, with entries for each input required in the GUI (Fig. 7).

Fig. 7: The project file format



```
  <?xml version="1.0" standalone="true"?>
- <verification>
  - <verification_unit>
    - <identifiers>
        <location_id>HMOS</location_id>
        <environmental_variable_id>Streamflow</environmental_variable_id>
        <additional_id>Mult1</additional_id>
      </identifiers>
    - <input_data>
      - <forecast_data_location>
          <file>D:\NOAA_work\HEP_projects\Ensemble_verification\EVS\EVS_releases\EVS_4.0\EVS_4.0_pre_release_tests\Spatial_agg\EVS_flow_ensemble_forecasts.fcst</file>
        </forecast_data_location>
        <observed_data_location>D:\NOAA_work\HEP_projects\Ensemble_verification\EVS\EVS_releases\EVS_4.0
          \EVS_4.0_pre_release_tests\Spatial_agg\EVS_flow_observations.obs</observed_data_location>
        <forecast_file_type>ASCII</forecast_file_type>
        <observed_file_type>NWS-CARD</observed_file_type>
        <forecast_time_system>UTC - 12 hours</forecast_time_system>
        <observed_time_system>Coordinated Universal Time (UTC)</observed_time_system>
      - <forecast_support>
          <statistic>INSTANTANEOUS</statistic>
          <existing_attribute_units>FEET CUBED/SECOND</existing_attribute_units>
          <notes/>
        </forecast_support>
      - <observed_support>
          <statistic>INSTANTANEOUS</statistic>
          <existing_attribute_units>FEET CUBED/SECOND</existing_attribute_units>
          <notes/>
        </observed_support>
        <use_all_observations_for_climatology>false</use_all_observations_for_climatology>
        <apply_date_cond_to_climatology>false</apply_date_cond_to_climatology>
        <apply_value_cond_to_climatology>false</apply_value_cond_to_climatology>
        <forecast_date_format>MM/dd/yyyy HH</forecast_date_format>
        <observed_date_format>MM/dd/yyyy HH</observed_date_format>
        <global_null_value>-999.0</global_null_value>
      </input_data>
    - <verification_window>
      - <start_date>
          <year>1997</year>
          <month>0</month>
          <day>1</day>
        </start_date>
      - <end_date>
          <year>2008</year>
          <month>11</month>
          <day>30</day>
        </end_date>
        <first_lead_period>0.0</first_lead_period>
        <last_lead_period>6.0</last_lead_period>
        <forecast_lead_units>DAY</forecast_lead_units>
        <sample_size_constraint>0.0</sample_size_constraint>
      </verification_window>
      <output_data_location>D:\NOAA_work\HEP_projects\Ensemble_verification\EVS\EVS_releases\EVS_4.0\EVS_4.0_pre_release_tests\Spatial_agg</output_data_location>
    - <paired_data>
        <paired_data_location>D:\NOAA_work\HEP_projects\Ensemble_verification\EVS\EVS_releases\EVS_4.0
          \EVS_4.0_pre_release_tests\Spatial_agg\HMOS_Streamflow_Mult1_pairs_raw.xml</paired_data_location>
        <eliminate_duplicates>true</eliminate_duplicates>
        <write_conditional_pairs>true</write_conditional_pairs>
        <write_unconditional_pairs>true</write_unconditional_pairs>
        <paired_write_precision>5</paired_write_precision>
        <strip_nulls_from_paired_file>true</strip_nulls_from_paired_file>
        <raw_pairs_in_aggregated_res>false</raw_pairs_in_aggregated_res>
      </paired_data>
    - <metrics>
      - <metric>
          <name>BrierScore</name>
          <probability_array_parameter>-Infinity,0.75,0.9</probability_array_parameter>
          <main_threshold>true, true, true</main_threshold>
          <threshold_condition>isGreater</threshold_condition>
```

First VU.

Some of the parameters of the first VU.

4.6 Command line options

Alongside the Java command line options (e.g. for allocating memory), the EVS provides several command line options for running an existing project file, together with utilities for converting between input data formats, which are summarized in Table 2.

Table 2: command line options in the EVS

Option	Example	Description
-p	-p in.xml out.asc	Converts a paired file, in.xml, to ASCII, out.asc
-aggOnly	-aggOnly	Executes the aggregation units only
-g	-g	Suppress the writing of graphics
-n	-n	Suppress the writing of numerics
-gui	-gui Project_1.evs	Open Project_1.evs in the EVS GUI.
-fcardtoasc	-fcardtoasc in.fsct out.fcst	Convert an NWS Card forecast file, in.fsct, to ASCII, out.fcst
-ocard2asc	-ocardtoasc in.obs out.obs	Convert an NWS Card observed file, in.obs, to ASCII, out.obs
-bin2asc	-obintoasc in.CS out.fcst	Convert an NWS CS binary forecast file, in.CS, to ASCII, out.fcst
-xslt	-xslt input.xml style.xml output	Convert input.xml to output (e.g. text) using the XSLT stylesheet, style.xml

4.7 Changing the format of the XML outputs from the EVS

The EVS outputs are strongly layered, and comprise results by forecast lead time and threshold, as well as for score decompositions and other secondary elements (e.g. the sharpness plot in a reliability diagram). In order to read the EVS outputs into a secondary application, it may be necessary to change the data format. The Extensible Stylesheet Language Transformation (XSLT) applies a transform to an XML document, allowing the data to be filtered, manipulated or transformed into another format, such as ASCII CSV or html. The transform is specified in a stylesheet. A description can be found here:

http://en.wikipedia.org/wiki/XSLT

The ability to manipulate or transform the XML outputs from the EVS into another format is implemented on the command line as follows:

```
java –jar EVS.jar –xslt input.xml style.xml output
```

where:

- xslt is the command to perform the transform;

- input.xml is the input xml file containing the EVS xml output data;
- style.xml is the XSLT style sheet in which the transform is specified; and
- output is the output location, such as a text file [an empty argument will print to standard out].

As indicated above, the transform is specified in the XSLT stylesheet, style.xml. This can be modified to extract any information required from the EVS output files and then re-directed to any output stream as necessary. An example of an XSLT transformation is provided in Appendix A2.

4.8 Creating custom plots of the EVS outputs in R

The numerical outputs from the EVS can be read into the R environment for statistical computing (www.R-project.org). A utilities script is provided in the `/nonsrc/rscripts` directory at the root of the installation. There are three methods for reading the different EVS outputs, namely `readEVSScores`, which reads the deterministic measures (e.g. mean error of the ensemble mean) and probabilistic verification scores (e.g. Brier score), `readEVSDiagrams`, which reads the verification diagrams (e.g. reliability diagram) and `readEVSBoxPlots`, which reads the EVS box plots. In addition to the utilities script, example scripts are provided in `/nonsrc/rscripts/example_scripts` for plotting specific (sets of) EVS metrics in R, including the plotting of sampling uncertainties (via confidence intervals).

5. A DETAILED GUIDE TO THE OPTIONS IN EACH WINDOW OF THE GUI

This section provides a guide to the options available in each window of the GUI.

5.1 Administrative functions in the main window

The opening window of the GUI, together with the Taskbar, is shown in Fig. 1. The opening window displays the verification units loaded into the software. The Taskbar is visible throughout the operation of the GUI and is used for administrative tasks, such as creating, opening, closing and saving a project. The Taskbar options are explained in Table 3. Shortcuts are provided on the Taskbar for some common operations, but all operations are otherwise accessible through the dropdown lists.

Table 3: Menu items

Menu	Function	Use
File	New project	Creates a new project
	Open project	Opens a project file (*.evs)
	Close project	Closes a project
	Save project	Updates or creates a project file (*.evs)
	Save project as	Updates or creates a named project file (*.evs)
	Exit	Exits EVS
Help	Messages on/off	Displays/hides tool tips
	Console	Shows the details of errors thrown
	About	Credits

All work within the EVS can be saved to a project file with the .evs extension. A new project is created with the **New project** option under the **File** dialog. An existing project is saved using the **Save** or **Save As**… options. These options are also available on the Taskbar. Project files are stored in an XML format and may be opened in a web browser or text editor. An example is given in Fig. 7.

5.2 The first window in the Verification stage

The first stage of an ensemble verification study requires one or more Verification Units (VUs) to be defined (Fig. 1). In this context, a VU comprises a time-series of a single variable at one location. The spatial scale or support of the variable is not identified in the EVS, but is assumed to be consistent for the observed and forecast data. For example, observations from a rain gauge should not, in general, be compared with precipitation forecasts averaged over a large grid cell. The actual spatial support may be arbitrarily small or large, but should be equivalent for the forecasts and observations. A VU is uniquely identified by a location ID, a variable ID and, optionally, an additional ID. These IDs must be entered in the first window, and are then displayed in the table and identifiers panel. A new VU may be added to the current project by clicking "**Add**" in the bottom left corner of the window (Fig. 1). This adds a VU with some default values for the identifiers. On entering multiple VUs, the basic properties of the *selected* VU (i.e. the item highlighted in the table) will be shown in the panels on the right. Existing units may be deleted or copied by selecting an existing unit in the table and clicking "**delete**" or "**copy**", respectively. On copying a unit, all of the properties of the unit are copied *except* the identifiers, which must be unique. This provides a convenient way to specify multiple units with the same verification properties (multiple segments to be verified for the same variable with the same temporal parameters).

The VU is defined by four different dialogs: identifiers (2a), input data (2b), time parameters (2c), and output data (2d).

2a. Set unit identifiers:

- Location identifier: an identifier denoting the location of the forecast point;
- Environmental variable identifier: an identifier denoting the environmental variable to be verified; and
- Additional identifier: arbitrary additional ID. For example, this may be used to distinguish between forecasts from different models for a common variable and location.

The names of the location and environmental variable are unrestricted (aside from a blank name or a name containing the character '.', which is used to separate the identifiers). Several default names for environmental variables are provided by right-clicking on the variable identifier box (Fig. 1).

2b. Identify input data sources:

- Files or folder containing forecast data: path to the folder containing the ensemble forecast files (and no other file types), or a file array chosen through the associated file dialog. *If possible, when the ensemble forecasts are distributed across multiple files, only those files that contain relevant forecasts should be selected, as all files must be processed before being checked against verification conditions* (e.g. if the files are separated by date, and a limited set of dates is subsequently defined);

- File containing observed data: path to concurrent observations of the forecast variable, which are used to verify the forecasts;
- File type: The file types for the ensemble forecasts and observations; and
- Time zones: the time zones for the forecasts and observations. The time zones are required for pairing (on the basis of date and time);

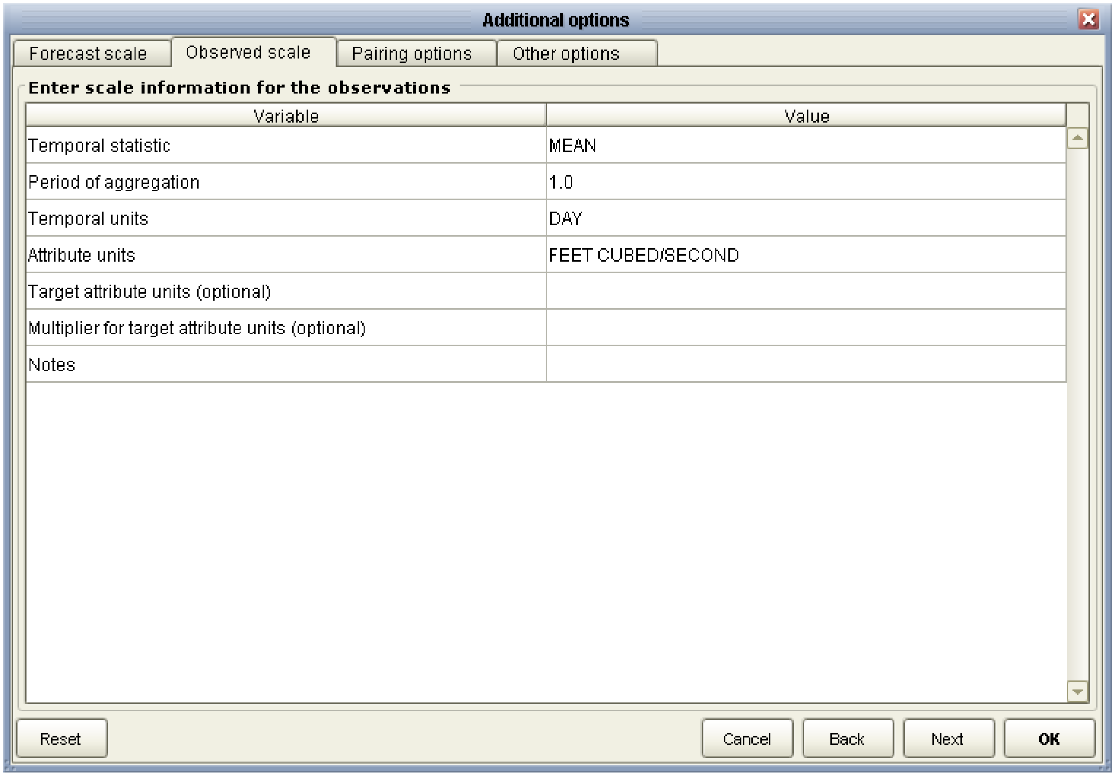
The paths to the observed and forecast data may be absolute or relative to the location of the EVS.jar. For example, a relative path beginning `..\` would denote the directory one level above the EVS.jar. Absolute paths may be entered manually or by clicking on the adjacent button, which opens a file dialog. Relative paths must be entered manually.

When conducting verification for the first time, the observations and forecasts are paired. These pairs are used to compute the differences between the observed and forecast values (i.e. the forecast 'errors') at concurrent times, i.e. the valid times. For subsequent work with the same VU, no pairing is necessary unless some of the input parameters that affect the pairs have changed (at which point, the pairs are deleted). The paired data are stored in an XML format, which may be opened in a web browser or text editor. Each forecast-observation pair is stored with a date in UTC (year, month, day, and hour of day), the forecast lead time in hours, the observed value, and the corresponding forecast ensemble members. A detailed explanation is also provided in the paired file header. An example of a paired file is given in Fig. 6. The EVS generates two paired files, for which writing is optional, namely the "raw" pairs and the "conditional" pairs.

The raw pairs comprise the paired forecasts and observations **after** any required change of support but **before** any changes in measurement units, temporal aggregation (of the pairs), or any other conditioning. The raw pairs are written to a file ending with `_pairs_raw.xml`. The values should match those contained in the original observed and forecast files (after any change of support). The conditional pairs comprise the paired forecasts and observations from which the verification metrics will be computed. The conditional pairs are written to a file ending with `_pairs_cond.xml`. By default, both the raw and conditional pairs are written to file. The paired files may be written in uncompressed ASCII or gzipped ASCII format.

In the EVS GUI, basic verification options are separated from more ‘advanced’ options, which are accessible through pop-up windows. For example, the “**More**” button within the Input data dialog opens a window for entering information about the scales at which the forecasts and observations are defined, among other things (Fig. 8a and Fig. 8b). Scale information includes the units of measurement (e.g. cubic feet/second) and temporal support at which the forecasts and observations are recorded (e.g. instantaneous vs. time-averaged). The forecasts and observations must be defined at equivalent temporal (and spatial) scales for a meaningful comparison between them. In the absence of user-defined information on the temporal scales, a warning message will be presented on conducting verification. This warning message is avoided if the temporal scale information is entered explicitly.

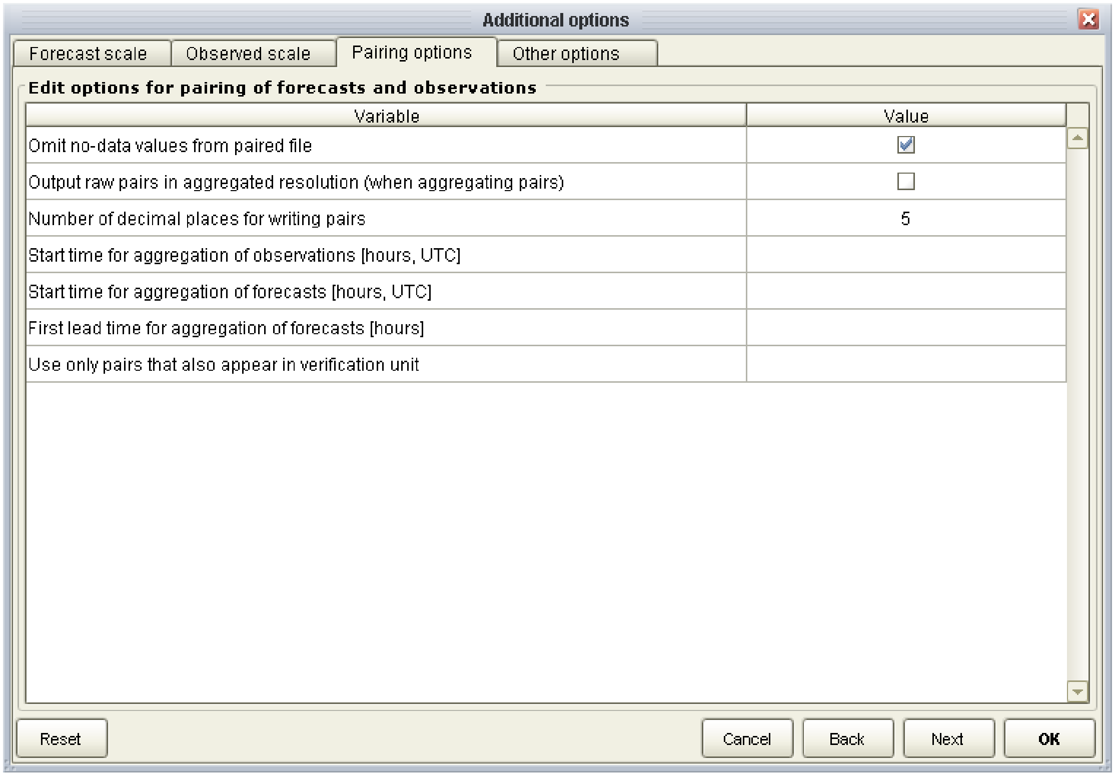
Fig. 8a: The Additional options dialog, accessed from the input data dialog



Enter scale information for the observations

Variable	Value
Temporal statistic	MEAN
Period of aggregation	1.0
Temporal units	DAY
Attribute units	FEET CUBED/SECOND
Target attribute units (optional)	
Multiplier for target attribute units (optional)	
Notes	

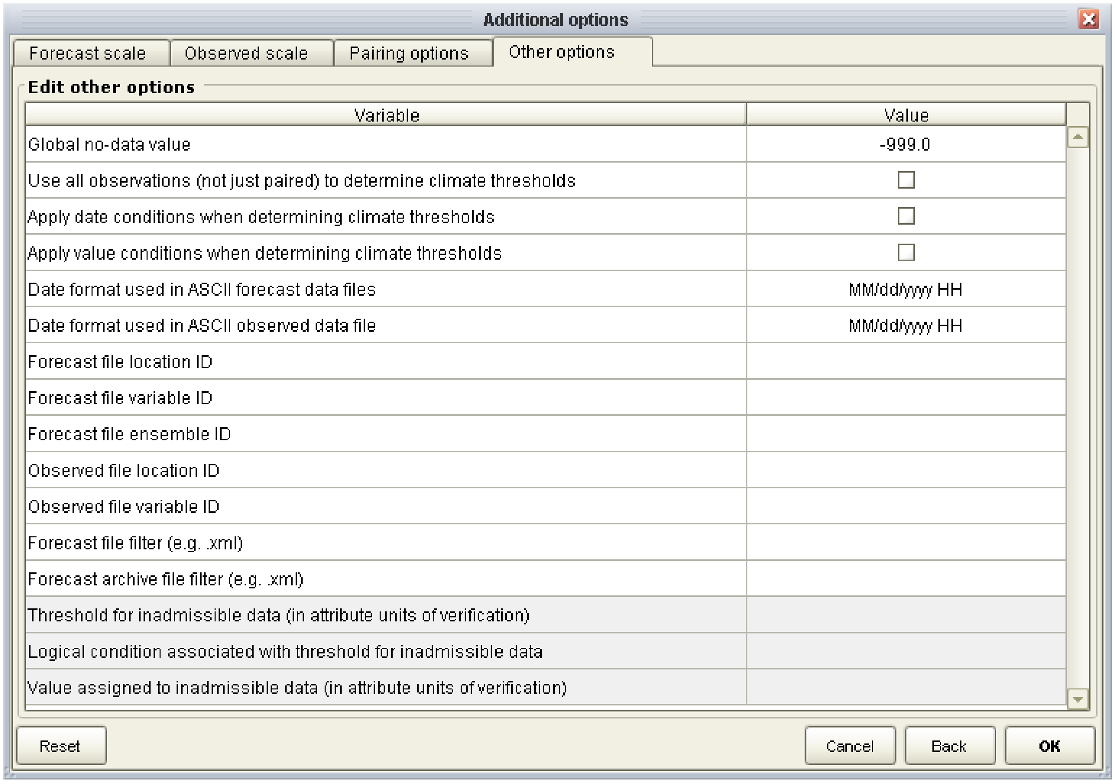
Fig. 8b: Pairing options (Additional options), accessed from the input data dialog



Edit options for pairing of forecasts and observations

Variable	Value
Omit no-data values from paired file	☑
Output raw pairs in aggregated resolution (when aggregating pairs)	□
Number of decimal places for writing pairs	5
Start time for aggregation of observations [hours, UTC]	
Start time for aggregation of forecasts [hours, UTC]	
First lead time for aggregation of forecasts [hours]	
Use only pairs that also appear in verification unit	

Fig. 8c: Other options (Additional options), accessed from the input data dialog



Edit other options

Variable	Value
Global no-data value	-999.0
Use all observations (not just paired) to determine climate thresholds	□
Apply date conditions when determining climate thresholds	□
Apply value conditions when determining climate thresholds	□
Date format used in ASCII forecast data files	MM/dd/yyyy HH
Date format used in ASCII observed data file	MM/dd/yyyy HH
Forecast file location ID	
Forecast file variable ID	
Forecast file ensemble ID	
Observed file location ID	
Observed file variable ID	
Forecast file filter (e.g. .xml)	
Forecast archive file filter (e.g. .xml)	
Threshold for inadmissible data (in attribute units of verification)	
Logical condition associated with threshold for inadmissible data	
Value assigned to inadmissible data (in attribute units of verification)	

In most cases, changes of scale should be conducted before using the EVS, but some options are provided internally. In particular, the measurement or "attribute" units of the forecasts or observations may be changed with some restrictions:

- Changes in attribute units are achieved by either: 1) specifying a named change from the current "`Attribute units`" to the "`Target attribute units`" (Fig. 8a); or 2) specifying a factor by which to multiply the current "`Attribute units`", in order to arrive at the "`Target attribute units`", namely the "`Multiplier for target attribute units`". Named changes of units (without manually defining a multiplier) are currently limited to:

  - `DEGREES (CELCIUS) <--> DEGREES (FAHRENHEIT);`
  - `MILLIMETRE <--> INCH`
  - `METRE <--> FEET`
  - `METRE CUBED/SECOND <--> FEET CUBED/SECOND`

In addition to changes in attribute units, there is some flexibility for verifying forecasts and observations with different temporal support *when the verification is desired at an aggregated level of support* (see the discussion below on temporal aggregation, and Fig. 9c). This is only possible under the following conditions:

1. The temporal support is `INSTANTANEOUS`, and the desired temporal aggregation involves a supported function (e.g. mean) over a period that is exactly divisible by the frequency of the data; and
2. The temporal support is the `TOTAL` over a specified period and the desired level of aggregation is a total over a longer period that is an exact multiple of the shorter period and the frequency of the data (e.g. verifying at a daily timestep when the observations are six-hourly totals, available every six hours).

Further control on the pairing of forecasts and observations is provided in the "Pairing options" tab of the "Additional options" dialog (Fig. 8b). The options comprise:

– <u>Omit no-data values from paired file:</u> the omission of null values from the paired files (default is TRUE);

– <u>Output raw pairs in aggregated resolution (when aggregating pairs):</u> in order to circumvent the large amount of RAM memory required for locations where the forecasts are much more resolved (e.g. hourly) than the temporal resolution required for verification (e.g. daily), this option allows for the paired data to be computed and stored in their aggregate (e.g. daily) resolution only. In this case, the forecast files are processed and aggregated individually (this is only beneficial when storing the data across multiple files), avoiding the need to read and store all forecasts at their native resolution. When using this option, any attempt to recompute verification results at a higher resolution than the resolution available in the aggregated pairs will result in the pairs being deleted and re-computed (possibly resulting in an out-of-memory error, unless sufficient memory is allocated to the reading of the observed and forecast data at their native resolution). By default the pairs are stored in their native resolution (FALSE);

- Number of decimal places for writing pairs: the number of decimal places for writing pairs (default is 5);
- Start time for aggregation of observations [hours, UTC]: if the observations comprise a finer scale or support than the forecasts, they must be aggregated prior to pairing. This parameter controls the start time in UTC at which to begin aggregating the observations (no default).
- Start time for aggregation of forecasts [hours, UTC]: if the forecasts comprise a finer scale or support than the observations, they must be aggregated prior to pairing. This parameter controls the start time in UTC at which to begin aggregating the forecasts (no default).
- First lead time for aggregation of forecasts [hours]: if the forecasts comprise a finer scale or support than the forecasts, they must be aggregated prior to pairing. This parameter controls the first lead time at which to begin aggregating the forecasts (no default).
- Use only pairs that also appear in verification unit: when comparing forecasts from two different systems, restrict the calculation of verification metrics to only those pairs that appear in the selected verification unit. This amounts to jointly pairing with another verification unit (no default).

The “Other options” tab of the “Additional options” dialog (Fig. 8c) contains further options for interpreting the input data, namely:

- Global no-data value: the global identifier for ‘null’ or missing values (i.e. values ignored throughout a verification study including metric calculation. The global no-data value is used to discriminate between valid and missing data internally and in the EVS outputs (e.g. verification pairs). For those input data sources that explicitly define the missing value, the global no data value replaces the original missing values. For those input data sources that do *not* explicitly define the missing value, any values that match the global no data value are interpreted as missing. By default, the no data value is -999.0 and only numeric missing values are accepted. Input data sources with a missing value are replaced with the global no data value, which cannot be NaN;

- Use all observations (not just paired) to determine climate thresholds: when conducting verification for thresholds whose values represent climatological probabilities, those climatological probabilities may be determined from the paired observations (FALSE) or all observations in the specified observed data source (TRUE). The default is FALSE, i.e. to use the paired observations only;
- Apply date conditions when determining climate thresholds: when conducting verification for thresholds whose values represent climatological probabilities, those climatological probabilities may be determined from the observations prior to applying any pre-conditions on the dates (FALSE) or afterwards (TRUE). Such preconditions may include the elimination of particular calendar months (see 2c. Set time parameters, below);
- Apply value conditions when determining climate thresholds: when conducting verification for thresholds whose values represent climatological probabilities, those climatological probabilities may be determined from the observations prior to applying any pre-conditions on their values (FALSE) or afterwards (TRUE). Such preconditions may include the elimination of observations that exceed a particular threshold (see 2c. Set time parameters, below);
- Date format used in ASCII forecast/observed data files: the date formats used for observations and forecasts in ASCII format (ignored for other file types). The dates are formed from the **case-sensitive** elements, yyyy (year), MM (calendar month), dd (day of month), HH (hour of day in the 24-hour clock), mm (minute of hour) and ss (second of minute) using appropriate, single-character, separators or whitespace (e.g. MM/dd/yyyy HH) or no separators (e.g. yyyyMMddHH). The default date format is MM/dd/yyyy HH;
- Forecast/observed file location ID: when reading XML and NetCDF files that contain specific location identifiers, the required location identifier may be defined explicitly or resolved to the VU location identifier (i.e. left blank, the default); and

- Forecast/observed file variable ID: when reading XML and NetCDF files that contain specific variable identifiers, the required variable identifier may be defined explicitly or resolved to the VU environmental variable identifier (i.e. left blank, the default).
- Forecast file ensemble ID: for those data sources that use an ensemble ID to discriminate between time-series (e.g. XML), the ensemble ID may be defined here. This is only required when the input data source contains more than one time-series with a given location ID and variable ID.
- Forecast file filter: when reading forecast files from a directory that contains multiple file types (e.g. including subdirectories), specify a string pattern (e.g. .xml) to read only those files that match the pattern (no filter by default).
- Forecast archive file filter: when reading forecast files from an archive that contains multiple file types (e.g. .tar.gz), specify a string pattern (e.g. .xml) to read only those files that match the pattern (no filter by default).
- Threshold for inadmissible data (in attribute units of verification); Logical condition associated with threshold for inadmissible data; and Value assigned to inadmissible data (in attribute units of verification): specify a constraint on admissible values of the forecasts and observations. The constraint is defined with a threshold and associated logical condition. When the constraint is met, the inadmissible values are replaced with the specified value. When a change in measurement units is requested, the detection limit is defined in the **target** measurement units of the forecasts and observations (i.e. in the units of the conditional paired data).

2c. Set time parameters:

- Start of verification period: the start date for verification purposes. This may occur before or after the period for which data are available. Missing periods will be ignored. The verification period is defined in UTC hours from 00 UTC on the input start date. The start date may be entered manually or via a calendar utility accessed through the adjacent button. In sub-selecting forecasts, the start of the verification period refers to the forecast valid date, not the forecast issue date;
- End of verification period: as above, but defines the last date to consider. The end date is also defined as 00 UTC on the specified date (i.e. add one day if the input date should be included in the verification window). In sub-selecting

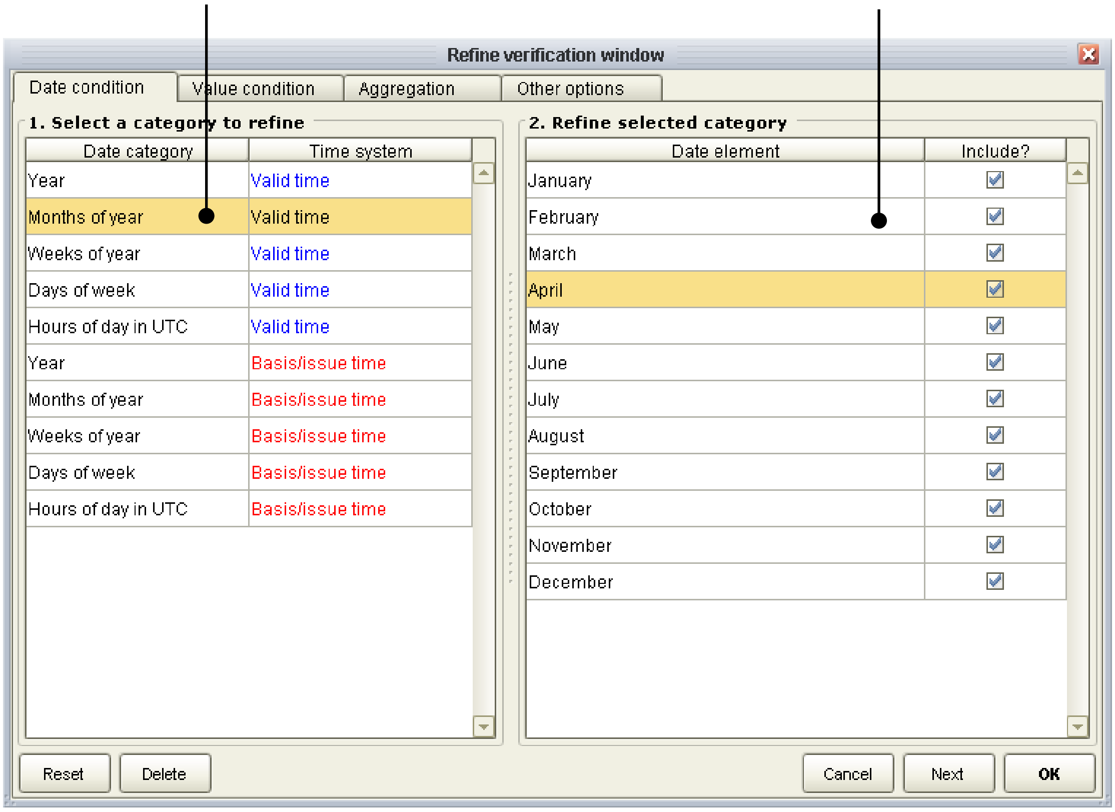
forecasts, the end of the verification period refers to the forecast valid date, not the forecast issue date;

- First lead time: the first forecast lead time (in given units) for which verification results will be computed;
- Last lead time: the last forecast lead time (in given units) for which verification results will be computed. Must be greater than the first lead time; and
- Aggregation period: the time period over which to aggregate the verification pairs. Aggregation removes short-range variability ("noise") by averaging over a period that matters for decision making purposes. For example, the verification pairs may be aggregated into ninety-day averages (assuming that the forecast time horizon is at least ninety days). When the temporal support of the forecasts and observations is different, verification may still be possible at an aggregated temporal support (see above). The aggregation period is applied to the *verification pairs* after any change of temporal support (of the forecast and observations) necessary to conduct pairing. For the same reason, changing the aggregation period will not delete existing pairs.

Fig. 9a: Dialog for refining verification window: conditioning with dates

Categories for refining dates considered

Consider only specific months



Refine verification window

1. Select a category to refine

Date category	Time system
Year	Valid time
Months of year	Valid time
Weeks of year	Valid time
Days of week	Valid time
Hours of day in UTC	Valid time
Year	Basis/issue time
Months of year	Basis/issue time
Weeks of year	Basis/issue time
Days of week	Basis/issue time
Hours of day in UTC	Basis/issue time

2. Refine selected category

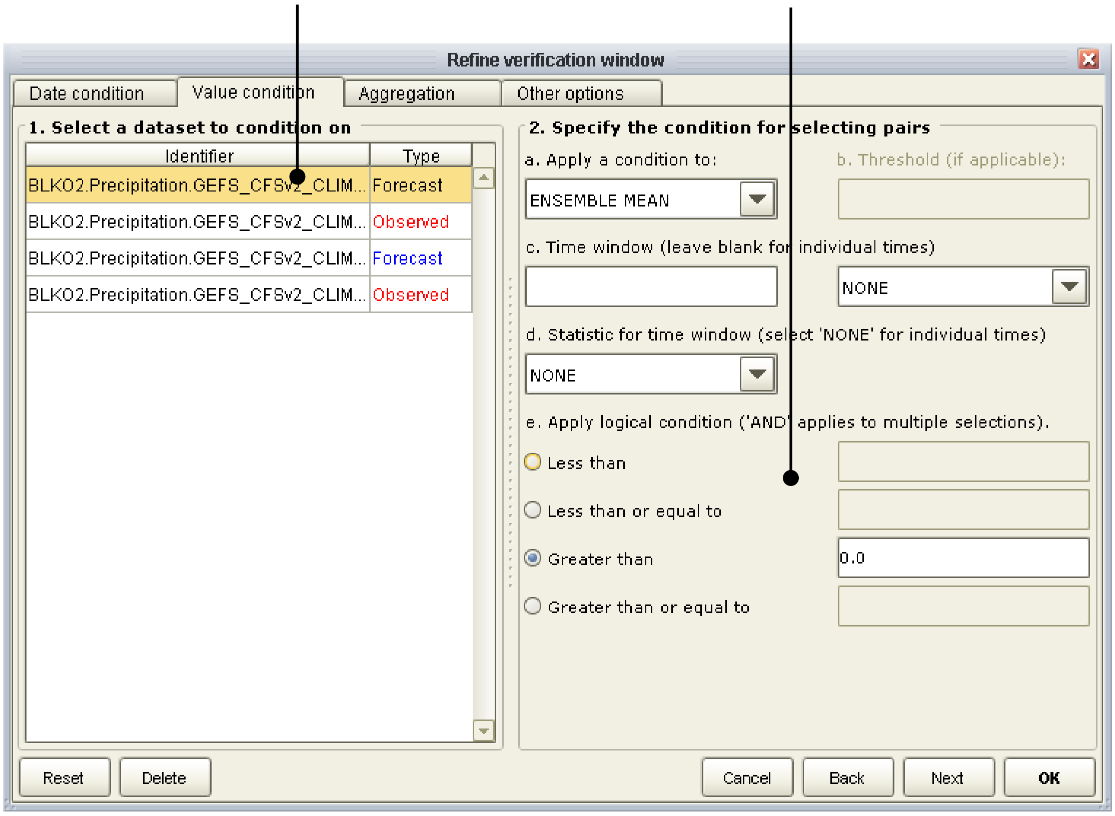
Date element	Include?
January	☑
February	☑
March	☑
April	☑
May	☑
June	☑
July	☑
August	☑
September	☑
October	☑
November	☑
December	☑

The verification window may be refined using various “pre-conditions” on the dates considered, as well as the size of the observed and forecast values included in the verification study. These options are accessed via the “**More**” button. For example, verification may be restricted to ‘winter months’ within the overall verification period, or may be limited to forecasts whose ensemble mean is below a given threshold (e.g. zero degrees for temperature forecasts). When conditioning on dates, the conditions may comprise forecast issue dates or forecast valid dates. When conditioning on variable value, the conditions may apply to the values of the current VU or another VU (e.g. select streamflow when precipitation is non-zero), providing the variables have the same prediction dates and intervals. Such conditioning may be relatively simple or arbitrarily complex depending on how many conditions are imposed simultaneously. However, there is a trade-off between the specificity of a verification study, which is increased by conditioning, and the number of samples available to compute the verification statistics, which is reduced by conditioning (i.e. sampling uncertainty is increased).

Fig. 9b: Dialog for refining verification window: conditioning with variable value

Variables available for conditioning

Forecast ensemble mean > 0



1. Select a dataset to condition on

Identifier	Type
BLKO2.Precipitation.GEFS_CFSv2_CLIM...	Forecast
BLKO2.Precipitation.GEFS_CFSv2_CLIM...	Observed
BLKO2.Precipitation.GEFS_CFSv2_CLIM...	Forecast
BLKO2.Precipitation.GEFS_CFSv2_CLIM...	Observed

2. Specify the condition for selecting pairs

a. Apply a condition to: ENSEMBLE MEAN

b. Threshold (if applicable):

c. Time window (leave blank for individual times) NONE

d. Statistic for time window (select 'NONE' for individual times) NONE

e. Apply logical condition ('AND' applies to multiple selections).

○ Less than

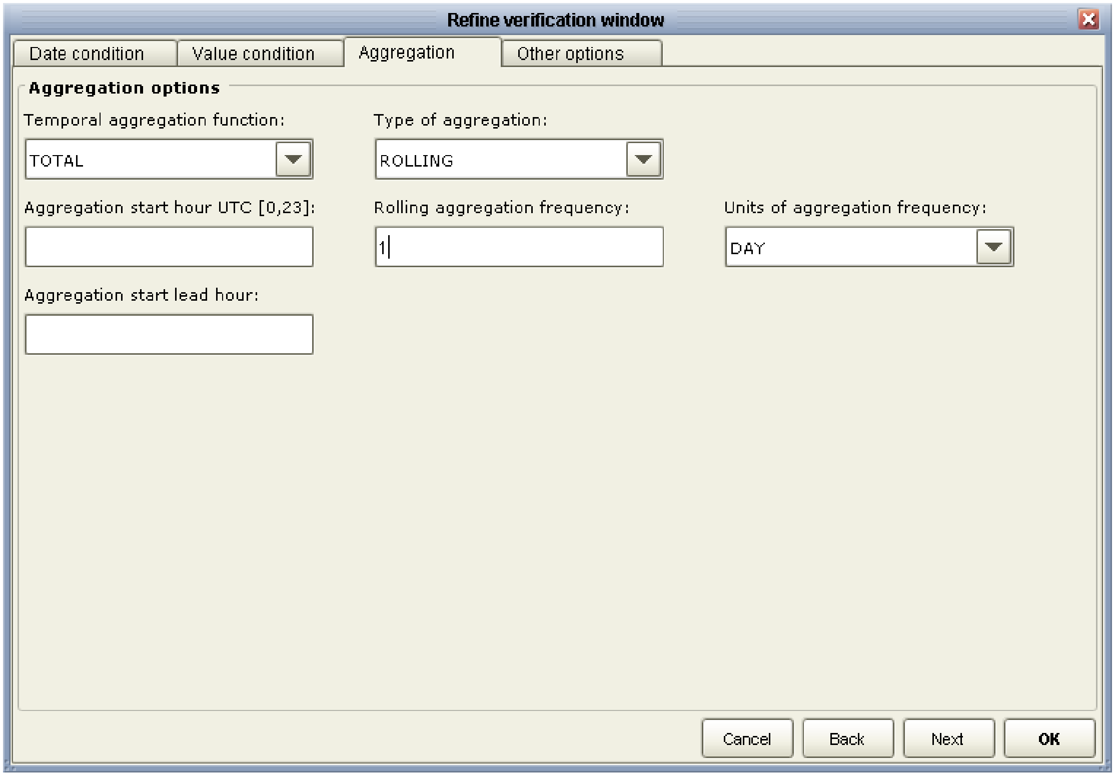
○ Less than or equal to

● Greater than 0.0

○ Greater than or equal to

The dialog for conditioning on date and variable value is shown in Fig. 9a and Fig. 9b, respectively. The conditions on dates or variable values entered in the verification window apply to all verification metrics computed for that VU. Alongside these pre-conditions, the individual metrics may be computed with respect to one or more threshold values, such as flows exceeding flood stage (see below). When designing a verification study, the pre-conditions used to sub-select pairs should be compatible with any discrete events that might be verified later. For example, it would *not* make sense to assess the quality of Probability of Precipitation (PoP) forecasts (using a discrete threshold for PoP) after removing all occurrences of zero precipitation via pre-conditions on the pairs. In contrast, it may make sense to eliminate "blown" forecasts (identified by conditions on variable values) before computing *any* verification metrics, including those for particular events.

Fig. 9c: Dialog for refining the verification window: aggregation options



Refine verification window

Aggregation options

Temporal aggregation function: TOTAL

Type of aggregation: ROLLING

Aggregation start hour UTC [0,23]:

Rolling aggregation frequency: 1

Units of aggregation frequency: DAY

Aggregation start lead hour:

Additional options for temporal aggregation are provided in the "Aggregation" section of the refinement dialog (Fig. 9c). These include:

– <u>Temporal aggregation function:</u> this allows for a temporal aggregation function to be defined. By default, aggregations requested in the main verification window involve a mean average over the specified period. This may be changed to a total (i.e. accumulation), minimum or maximum value, among others;

- Aggregation start hour UTC: the time of day in hours UTC [0,23] at which temporal aggregation begins. By default, aggregation begins at the first available verification pair (i.e. the start of the time-series of forecasts and observations that cover a given forecast ensemble trace);
- Aggregation start lead hour: the forecast lead time in hours at which to begin temporal aggregation. By default, aggregation begins at the first available forecast lead time;
- Type of aggregation; Rolling aggregation frequency; and Units of aggregation frequency: by default, temporal aggregation is conducted without overlapping periods (BACK-TO-BACK). Optionally, however, a ROLLING aggregation may be performed with a given frequency and associated temporal units. For example, parameter values of ROLLING, 1 and DAY would conduct a rolling aggregation with the specified aggregation period (defined in 2c. Set time parameters) at an interval of 1 day between aggregations.

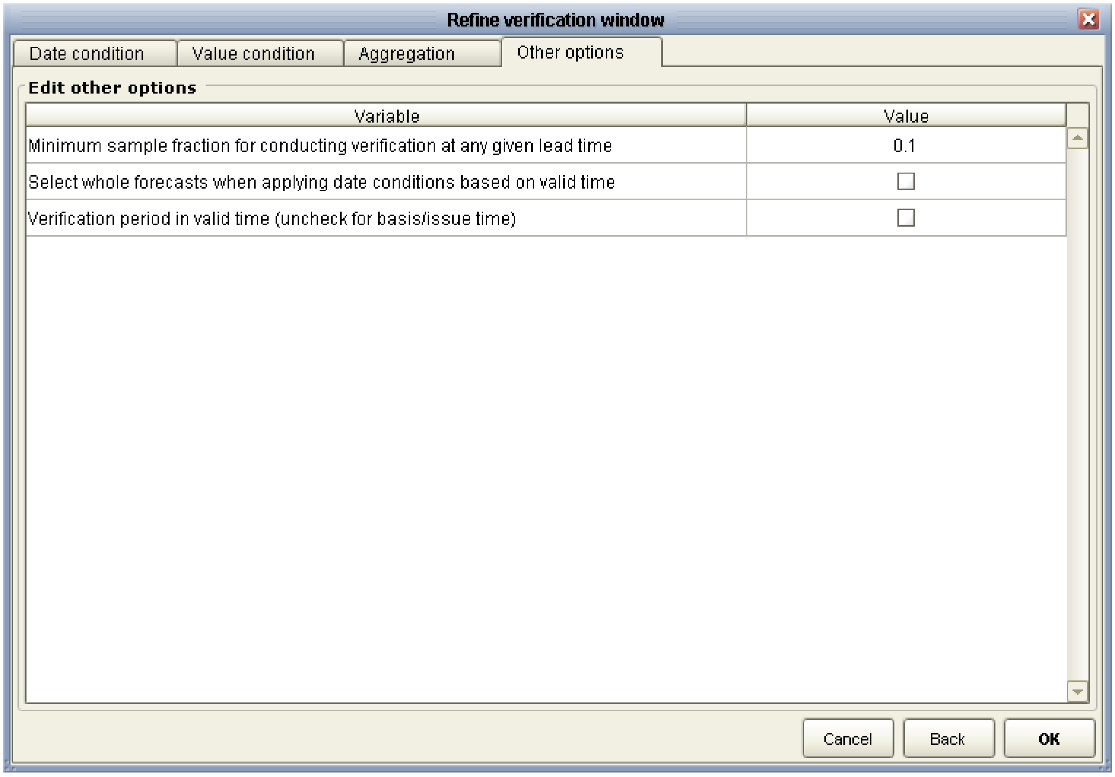
The "Other options" section of the refinement dialog (Fig. 9d) comprises the following options:

- Minimum sample fraction: this allows for the specification of a minimum sample size per forecast lead time for computing verification results. The sample size constraint is set by a fraction in the range [0,1]. The fraction is multiplied by the average number of pairs across all lead times to determine the minimum sample size as a numbers of pairs. For example, a fraction of 0.5 implies that verification results will *not* be computed for any lead time with fewer than 50% of the average number of pairs across all lead times;
- Select whole forecasts when applying date conditions based on valid time: when interpreting conditions on valid date and time, only those forecasts and observations whose valid dates and times that meet the conditions are included (FALSE). Thus, when part of the forecast horizon falls outside of these constraints, the forecasts are curtailed. Optionally, whole forecasts may be selected by the constraints on valid time; that is, for a given forecast, all forecast valid dates and times are selected when any one of those times meets

the constraints (TRUE). By default, only those forecasts and observations whose valid dates and times that meet the conditions are included (FALSE);

- Verification period in valid time: by default the start and end dates of the verification period are interpreted in valid time (TRUE). Optionally, however, they may be interpreted in basis/issue time (FALSE). In that case, only those forecasts and observations issued within the verification period will be included.

Fig. 9d: Dialog for refining the verification window: other options



Variable	Value
Minimum sample fraction for conducting verification at any given lead time	0.1
Select whole forecasts when applying date conditions based on valid time	☐
Verification period in valid time (uncheck for basis/issue time)	☐

2d. Set location for output data:

- Folder for output statistics: path to the folder for writing the paired files and the verification output data generated by the system, if written output is requested (see below).
- A “**More**” button, which opens an advanced options dialog with options to:
  - Write conditional pairs: write the conditional pairs (TRUE, by default).
  - Write unconditional pairs: write the unconditional pairs (TRUE, by default).
  - Write pairs in compressed (gzip) format: gzip all written pairs (FALSE, by default).

5.3 The second window in the Verification stage

The second window in the Verification stage is shown in Fig. 2 and is accessed by clicking "**Next**" from the first window (Fig. 1). The second window shows the verification metrics available for the VU selected in the first window.

The EVS includes single-valued measures, which can be used to verify the ensemble average forecast (mean, median or mode), and statistics that measure the quality of the forecast probabilities. While single-valued measures cannot verify the forecast probabilities, they are useful for evaluating the "best estimate" from the ensemble forecast. Currently, the single-valued measures available in the EVS include the mean error, the RMSE, the mean absolute error, the relative mean error, and the coefficient of correlation between the ensemble average forecast and observed values. Table 4 lists the metrics available in the EVS, which contain varying levels of detail about forecast quality. Some of the ensemble verification metrics verify discrete events, such as the (non-)exceedence of a particular threshold (e.g. flood stage), whereas other metrics evaluate the forecasting errors across all possible thresholds. Further information about the metrics available in the EVS can be found in Section 6 and Appendix A1. Examples of their interpretation can be found in Section 7.

Table 4: summary of the verification metrics available in the EVS

Metric name	Quality attribute tested	Discrete events?	Detail
Sample size	None	N/A	N/A
Correlation coefficient	Ensemble average (deterministic)	No	Lowest
Mean error	Ensemble average (deterministic)	No	Lowest
Relative mean error	Ensemble average (deterministic)	No	Lowest
Mean absolute error	Ensemble average (deterministic)	No	Lowest
RMSE	Ensemble average (deterministic)	No	Lowest
Brier Score	Lumped error score	Yes	Low
Brier Skill Score	Lumped error score vs. reference	Yes	Low
Mean CRPS	Lumped error score	No	Low
Mean CRPSS	Lumped error score vs. reference	No	Low
ROC score	Lumped discrimination score	Yes	Low
Mean error of prob. diag.	Reliability (unconditional bias)	No	Low

Mean capture rate diag.	Probability of real-valued error	No	High
Rank histogram	Reliability (conditional bias)	No	High
Spread-bias diagram	Reliability (conditional bias)	No	High
Reliability diagram	Reliability (conditional bias)	Yes	High
ROC diagram	Discrimination	Yes	High
Modified box plots	Error visualization	No	Highest

On selecting a given metric in the table, information about that metric is provided in the top right dialog, and the parameters of the metric are displayed for entering/editing in the bottom-left panel. A metric is included, and its parameter values are enabled for editing, by checking the box adjacent to the metric in the top left table. The parameters of each metric are listed in Table 5. After modifying the verification statistics and their parameters, the new information is saved to the current unit by clicking "**Save**".

Table 5: Parameters for each verification metric

Metric	Parameter (and type)	Meaning
Mean Error	Thresholds **(basic)**	Produces the metric for each subset of data specified by the threshold. The thresholds may be defined in real units or in probabilities. By default, they refer to non-exceedence probabilities from the observed climatology.
	Ignore conditions on variable value **(advanced)**	Any conditions on the observed or forecast values used to subset pairs (an advanced option in the verification window) will be ignored for this metric.
	Average of ensemble members **(advanced)**	Select the desired average of the ensemble member values to verify. Options include the ensemble mean, median and mode values. By default, the ensemble mean is verified.
	Threshold values are non-exceedence climatological probabilities **(advanced)**	If this parameter is true (checked; the default option), the threshold parameter (above) will refer to non-exceedence probabilities in the climatological probability distribution. For example, a threshold value of 0.2 would select pairs using the real value corresponding to probability 0.2 in the climatological probability distribution. The form of the relationship will depend on the logical condition for the threshold. If this parameter is false (unchecked), the thresholds are interpreted as real-values in observed units (e.g. cubic feet per second).

	Logical condition for event threshold **(advanced)**	Changes the logical condition for any thresholds used to subset data. For example, if the logical condition is “greater than”, only those forecast - observation pairs whose observed values are greater than the threshold will be used.
	Lower bound on thresholds (real value) **(advanced)**	Specify a lower bound on the thresholds for which verification metrics will be computed in units of the paired data (after applying any change of units).
	Upper bound on thresholds (real value) **(advanced)**	Specify an upper bound on the thresholds for which verification metrics will be computed in units of the paired data (after applying any change of units).
Root Mean Square Error	Same as mean error	Same as mean error.
Relative mean error	Same as mean error	Same as mean error.
Mean Absolute Error	Same as mean error	Same as mean error.
Correlation Coefficient	Same as mean error	Same as mean error.
Brier score	Same as mean error	Same as mean error.
	Select score decomposition **(advanced)**	The Brier Score may be decomposed into the calibration-refinement (CR) and/or the likelihood-base-rate (LBR) factors. In terms of the CR, the overall score comprises reliability - resolution + uncertainty. In terms of the LBR, it comprises Type-II conditional bias – discrimination + sharpness.
Brier Skill Score	Same as Brier Score	Same as Brier Score.
	Reference forecast for skill **(advanced)**	Allows a reference forecast to be selected for use in the skill calculation. The reference forecast must be loaded into the EVS as another VU. By default, the reference forecast is sample climatology.
Mean Continuous Ranked Probability Score	Same as mean error	Same as mean error.
	Select score decomposition **(advanced)**	Allows for the calibration-refinement decomposition of the overall score into contributions due to (lack of) reliability, resolution and uncertainty (climatological variability). The overall score comprises reliability - resolution + uncertainty.
Mean Continuous Ranked Probability Skill Score	Same as Mean Continuous Ranked Probability Score	Same as Mean Continuous Ranked Probability Score.
	Reference forecast for skill **(advanced)**	Same as parameter for Brier Skill Score.

Mean Error of Probability diagram	Same as mean error	Same as mean error.
	Number of points in diagram **(advanced)**	Sets the number of equally-spaced probability values (from 0-1) for which the metric will be computed and plotted.
Mean Capture Rate Diagram	Same as Mean Error of Probability diagram	Same as Mean Error of Probability diagram.
Modified box plot pooled by lead time	Ignore conditions on variable value **(advanced)**	Same as parameter for mean error.
	Number of points in diagram **(advanced)**	Sets the number of equally-spaced probability values (from 0-1) at which the boxes will be computed and plotted. The middle thresholds form the boxes and outer thresholds form the whiskers.
Modified box plot per lead time by observed value	Same as modified box plot pooled by lead time	Same as modified box plot pooled by lead time.
Modified box plot per lead time by forecast value	Same as modified box plot pooled by lead time	Same as modified box plot pooled by lead time.
	Average of ensemble members **(advanced)**	Function to determine the average forecast value from the ensemble members, against which to order and plot the boxes. Possibilities include the mean, median and mode.
Relative Operating Characteristic	Same as Mean Error of Probability diagram	Same as Mean Error of Probability diagram.
	Fit a smooth function to empirical ROC **(advanced)**	If this parameter is true (checked; not the default option), the binormal approximation will be used to model the bivariate distribution of the Probability of Detection (PoD) and Probability of False Detection (PoFD). The empirical pairs of PoD and PoFD are provided alongside the binormal model fit. If this parameter is false, only the empirical pairs of PoD and PoFD will be provided.
Relative Operating Characteristic Score	Same as Mean Error of Probability diagram	Same as Mean Error of Probability diagram.
	Reference forecast for skill **(advanced)**	Same as parameter for Brier Skill Score.
	Fit a smooth function to empirical ROC **(advanced)**	Same as parameter for Relative Operating Characteristic.

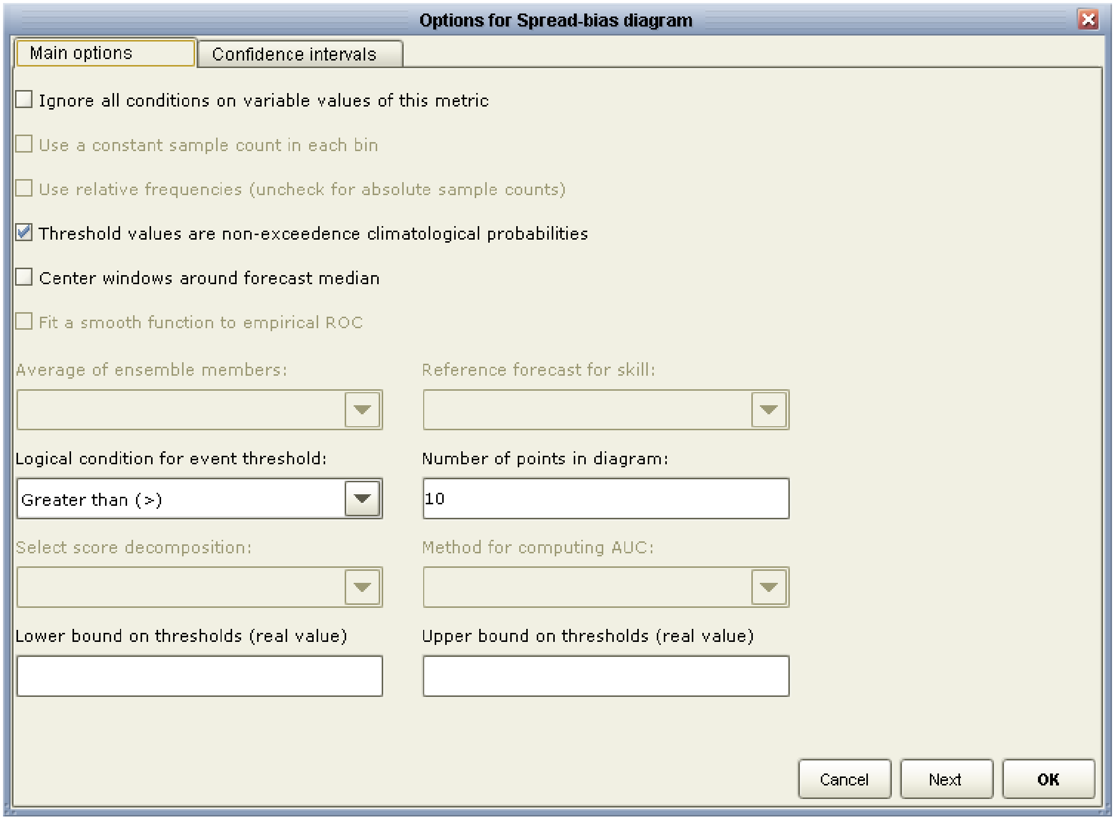
	Method for computing AUC **(advanced)**	Sets the method for computing the Area Under the Curve (AUC). By default, the trapezoid rule is used to integrate the Relative Operating Characteristic curve based on the specified number of points. Optionally, the score may be computed using the algorithm from Mason and Graham (2000).
Reliability Diagram	Ignore conditions on variable value **(advanced)**	Same as parameter for mean error.
	Use a constant sample count in each bin **(advanced)**	If this parameter is false (unchecked; the default option), the forecasts probability bins for which the reliability values are computed will take a fixed width in the range 0-1 depending on the number of points requested for the diagram (below). If this parameter is true (checked), the forecast probability bins for which the reliability values are computed will vary in width such that each bin captures the same number of forecasts.
	Threshold values are non-exceedence climatological probabilities **(advanced)**	Same as parameter for mean error.
	Logical condition for event threshold **(advanced)**	Same as parameter for mean error.
	Number of points in diagram **(advanced)**	Sets the number of probability bins (from 0-1) for which the metric will be computed and plotted. These bins may capture an equal sample count (see above) or may be equally spaced.
Rank histogram	Ignore conditions on variable value **(advanced)**	Same as parameter for mean error.
	Use relative frequencies (uncheck for abs. sample counts) **(advanced)**	If this parameter is true (checked, the default), the rank histogram will show the fraction of observations that fall between each ensemble member, otherwise it will show the absolute number of observations.
	Threshold values are non-exceedence climatological probabilities **(advanced)**	Same as parameter for mean error.
	Logical condition for event threshold **(advanced)**	Same as parameter for mean error.
Spread-Bias Diagram	Ignore conditions on variable value **(advanced)**	Same as parameter for mean error.
	Threshold values are non-exceedence climatological probabilities **(advanced)**	Same as parameter for mean error.

	Center windows around forecast median **(advanced)**.	If this parameter is false (unchecked; the default option), the probability of an observation falling within a forecast bin is determined for bins separated by probabilities within the forecast distribution. For example, if the parameter for the 'Number of points in the diagram' (see below) is 10, probabilities will be determined for bins representing deciles of the forecast. If this parameter is true (checked), probabilities of the observation falling within a forecast bin will be determined for symmetric forecast bins defined with respect to the forecast median.
	Logical condition for event threshold **(advanced)**.	Same as parameter for mean error
	Number of points in diagram **(advanced)**.	Defines the number of forecast bins for which the probability of an observation falling within that bin is determined.

Most of the ensemble verification metrics compare the observed and forecast values at specific thresholds. In some cases, these thresholds define a subset of data from which the metric is calculated. Most of the metrics can be computed from *all* data, as well as subsets of data defined by the thresholds. Other metrics verify only discrete events within the continuous forecast distributions. For example, the reliability diagram, relative operating characteristic and the Brier score, *require* one or more thresholds to be defined, and cannot be computed from all data. For these metrics, the thresholds represent cutoff values from which discrete events are computed. By default, the thresholds refer to non-exceedence probabilities within the climatological probability distribution and must, therefore, cover an interval of [0,1]. For example, a threshold of 0.2 would refer to all pairs whose observed values have an eighty percent chance of being exceeded, on average. The climatological probability distribution is computed from the observed (sample) data provided in the first verification window and is, therefore, subject to sampling uncertainty. The thresholds can be edited and added or deleted manually, via the table of thresholds, or semi-automatically by specifying a positive number of thresholds, the first threshold, and a non-zero increment between thresholds (positive to increase from the first threshold, negative to decrease). The types of thresholds may be modified via the "**More**" button, which displays an advanced options dialog. For example, the thresholds may be changed to real-values, rather than probabilities (e.g. flood stage) and the logical condition can be changed to non-exceedence, among others (see below also).

Depending on the selected verification metric, there are additional, advanced, parameters that can be altered. These parameters are available through the **"More"** button when a particular metric is selected. The parameter options comprise two tabbed panes (Fig. 10a), one comprising the "main options" for a particular metric and one comprising the options for computing confidence intervals (Fig. 10b). For example, when computing ensemble metrics using thresholds, the thresholds may be treated as non-exceedence (<, <=) or exceedence (>, >=) thresholds, which may be useful for exploring low- versus high-flow conditions, respectively (Fig. 10a). The parameter options for each metric are summarized in Table 3. A 'basic' parameter is accessed through the main window in EVS, while an 'advanced' parameter is accessed through the "**More**" button (as in Fig. 10a).

Fig. 10a: Advanced parameter options for a selected metric (ROC in this case)



□ Ignore all conditions on variable values of this metric

□ Use a constant sample count in each bin

□ Use relative frequencies (uncheck for absolute sample counts)

☑ Threshold values are non-exceedence climatological probabilities

□ Center windows around forecast median

□ Fit a smooth function to empirical ROC

Average of ensemble members:

Reference forecast for skill:

Logical condition for event threshold: Greater than (>)

Number of points in diagram: 10

Select score decomposition:

Method for computing AUC:

Lower bound on thresholds (real value)

Upper bound on thresholds (real value)

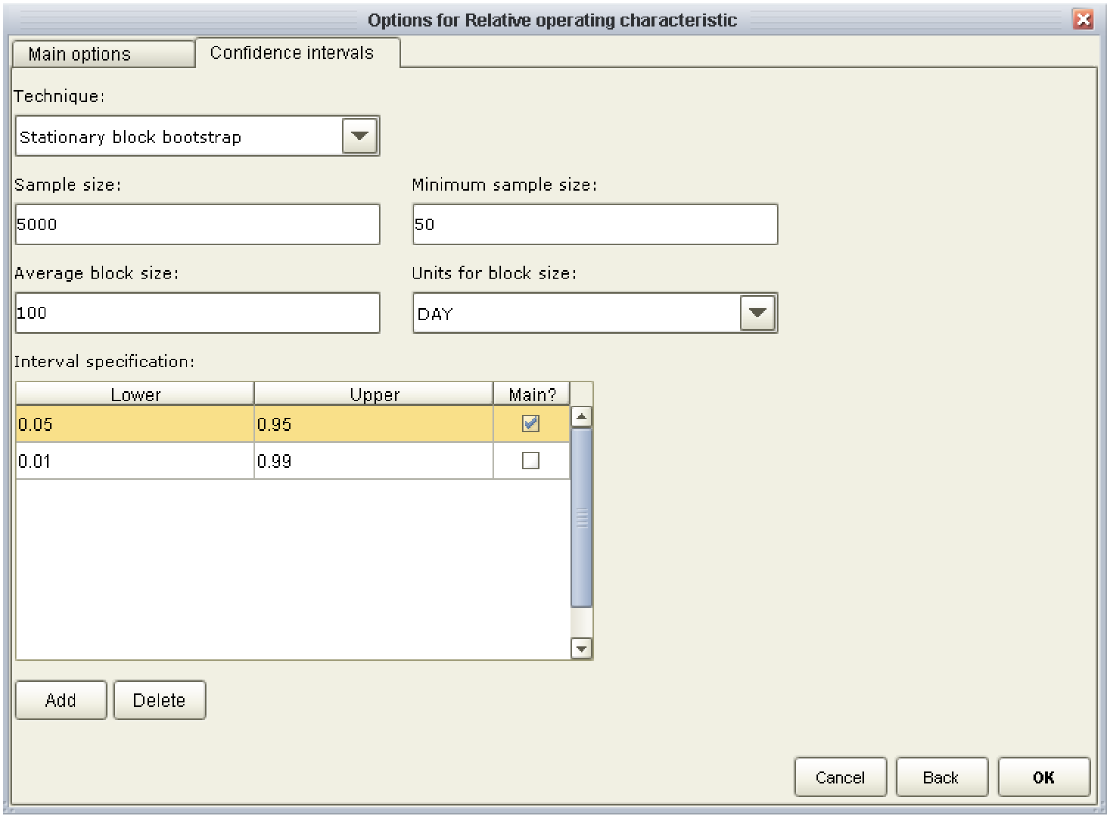
Confidence intervals can be computed for any of the verification metrics within the EVS, except for the box plots. In future, knowledge of the sampling distributions of particular verification metrics may be incorporated into the EVS. Currently, however, confidence intervals are derived numerically using a common algorithm for all metrics, namely the stationary block bootstrap (Fig. 10b). The parameters for deriving the confidence intervals are:

- Technique: select “none” (default) to omit confidence intervals from the verification results and “Stationary block bootstrap” to use the stationary block bootstrap (Politis and Romano, 1994);
- Sample size: The number of bootstrap samples to use in computing the confidence intervals. Each sample represents one bootstrap configuration of the verification pairs and associated metric calculation. Using more samples implies a better estimate of the confidence interval, but (potentially much) greater computational time. Also, bootstrapping is a resampling procedure and thus inherently constrained by the available verification pairs (sample size/diversity). In general, somewhere between 1000 and 10000 bootstrap samples may be appropriate (which implies between 1000 and 10000 computations of the chosen metric at all required thresholds);
- Minimum sample size: the minimum number of samples required in order to compute confidence intervals. If fewer than the required number of samples are found, the intervals will be omitted. The sample size constraint applies to a specific metric and (un)conditional sample. For example, when computing the unconditional mean error (mean error for “All data”) at a particular forecast lead time, the minimum sample size should exceed the total number of verification pairs available (after applying any pre-conditions). When computing the reliability diagram for a particular forecast lead time and threshold, the confidence intervals will be computed for each forecast probability bin in which the minimum sample size was exceeded. Thus, depending on the minimum sample size and metric, confidence intervals may be displayed for none, some, or all of the metric results at a given forecast lead time. Also, depending on the bootstrap samples generated, the actual number of samples that meet the minimum requirements (and hence the presence and appearance of the confidence intervals) will vary each time the bootstrapping is repeated. In general, a minimum sample size of 50 is reasonable;
- Average block size: the stationary block bootstrap attempts to account for temporal statistical dependence by randomly sampling contiguous ‘blocks’ of verification pairs that may be assumed statistically independent given the average block length. The blocks are sampled from a geometric probability distribution, which is completely defined by its mean (the average block length). The central time index of each block is sampled from a discrete uniform distribution whereby each time in the paired sample is equally probable. A single bootstrap sample comprises a resampled paired dataset with an equal

number of pairs to the original dataset. When computing confidence intervals for several VUs, the component VUs may be assumed statistically dependent or statistically independent (see Section 5.4);

- Units for block size: the time units for the average block size; and
- Interval specification: confidence intervals are computed from the bootstrap sample of metric values. One or more intervals may be defined by their lower and upper limits (e.g. [0.05,0.95]). Optionally, one interval can be selected for display in the graphical outputs by denoting that interval a “main” interval. All intervals are written to the numerical outputs (XML).

Fig. 10b: Confidence intervals for a selected metric (ROC in this case)



Options for Relative operating characteristic

Technique: Stationary block bootstrap

Sample size: 5000

Minimum sample size: 50

Average block size: 100

Units for block size: DAY

Interval specification:

Lower	Upper	Main?
0.05	0.95	☑
0.01	0.99	□

All of the information necessary to verify the ensemble forecasts is now available, and verification may be performed by clicking “**Run**” for the current VU or “**Run all**” to execute all VUs in the current project. A progress dialog is then displayed. The progress dialog provides options to cancel processing, to minimize (iconify) the GUI, and to show further details of any errors thrown during processing. Processing may take several minutes or longer (i.e. hours or even days), depending on the size of the project. If not already available, the paired files are created (see above) and the selected metrics are then computed for each unit. No products are displayed or written at this stage; instead the numerical results are stored in memory, in preparation for generating these products in the Output window (see Section 5.5).

5.4 The Aggregation window

Alongside verification of ensemble forecasts from a single point or area, it is possible to aggregate verification statistics across multiple locations (e.g. for precipitation across multiple river basins). This is achieved in the aggregation window (Fig. 3). By default, a potential aggregation unit (AU) is added for each set of VUs that are fully defined and comparable for the purposes of aggregation. If no AUs are displayed, there are no fully defined VUs that are comparable. Additional AUs may be derived by copying one of the default AUs using the "**Copy**" button (Fig. 3). In this way, AUs can be derived for each possible combinations of the component VUs. A VU is fully defined for the purposes of aggregation if the following parameters are set:

- The unique identifiers for each VU;
- The verification period, comprising the start and end dates;
- The time systems in which the forecasts and observations are recorded;
- A valid output directory for each VU; and
- One or more verification metrics.

Two or more VUs are comparable if the following parameters are equal:

- The first and last lead times;
- The aggregated resolution of the verification pairs, including the aggregation period and function;
- The support of the forecasts (after applying any required change of support);
- The support of the observations (after applying any required change of support); and
- The verification metrics and their associated parameter values.

If one or more of these parameters is undefined, the VUs are deemed provisionally comparable, but the aggregation may fail at run time.

The properties of an AU may be viewed or edited by selecting an AU in the table. Each AU is given a default identifier, which may be altered by the user. Multiple AUs may be defined in one project to generate aggregate statistics from various groups of

VUs with common verification parameters (see below). On selecting a particular AU, a list of candidate VUs appears under “Verification units to include in aggregation” and the common properties of those VUs appear under “Common parameter values”. Two or more VUs must be selected to perform aggregation. The output folder in which the aggregated statistics will be written appears under “2c. Set location for output data”. After defining one or more AUs, aggregation is performed by clicking “**Run**.”

Editing of the VUs upon which one or more AUs is based will result in a warning message and the option to either remove the edited VU from each of the AUs to which it belongs or to cancel the edits.

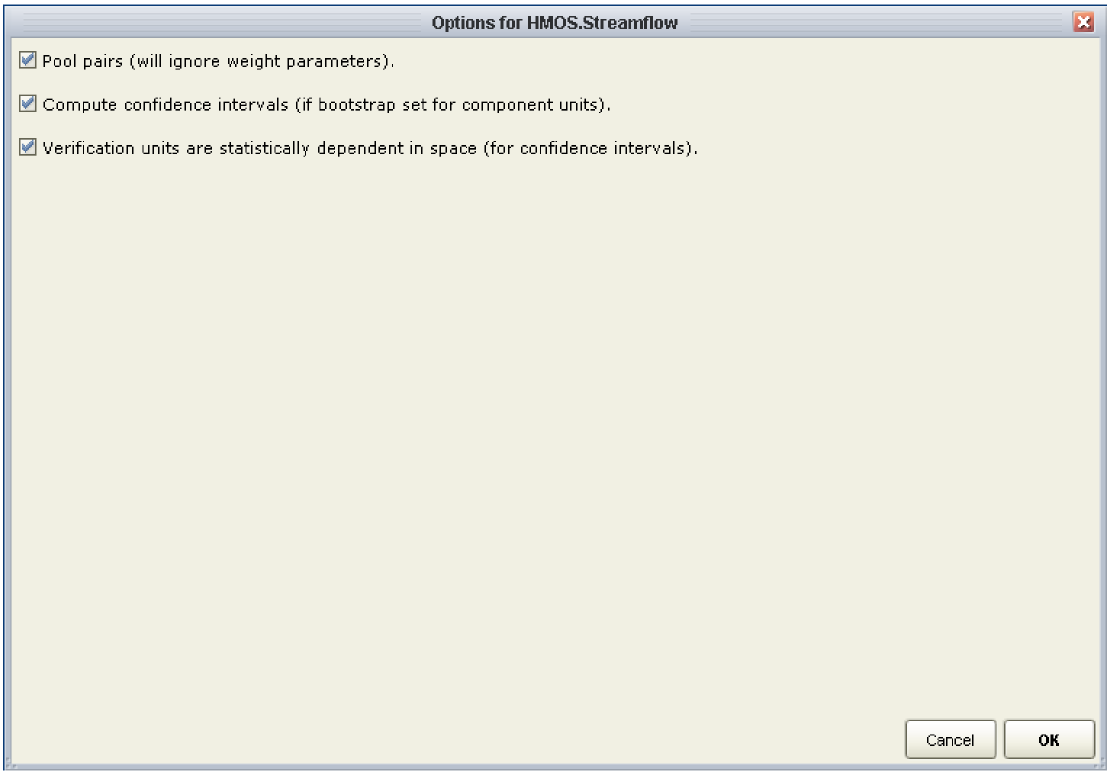
Aggregation is achieved by either: 1) averaging the verification results from the input metrics or: 2) by pooling the verification pairs. Averaging of the outputs is preferred over pooling of the input pairs for reasons of computational efficiency (especially when pooling across many VUs), but pooling of pairs is preferred when the verification metrics are not a simple (linear) function of the data (e.g. the correlation coefficient and most other metrics in the EVS). Pooling of pairs is required when computing confidence intervals for an AU (in general, this is extremely time-consuming). Averaging comprises a weighted sum of the input metrics from the individual VUs, with user-defined weights that sum to 1.0. For verification metrics that comprise binned statistics (e.g. the reliability diagram; see below), the sample means are computed for each bin in turn. For verification statistics that are conditional upon one or more event thresholds, the statistics are averaged across the same thresholds at each location. The weights assigned to each VU must be within [0,1] and the sum of all weights must be equal to 1. By default, equal weights are assigned to each VU, but unequal weights may be input manually or a value of ‘S’ defined to weigh by the relative sample size at the first forecast lead time (maintaining constant weights across lead times).

The default approach to spatial aggregation adopted in the EVS is somewhat pragmatic. In general, computing the average of a set of metrics (outputs) will not produce the same results as computing the metric from the pooled inputs, i.e. the pooled pairs. The option to pool pairs, rather than average metrics, is available in the advanced options dialog, which is accessed by the “**More**” button in the aggregation window (Fig. 3).

The advanced options are shown in Fig. 11 and comprise:

- Pool pairs: if selected (default is not selected), the verification metrics will be computed from the *pooled pairs*, otherwise they will be computed from the *pooled verification results* (i.e. a weighted averaged). When pooling pairs, the weights associated with the VUs in the main aggregation window (Fig. 3) will be ignored;
- Compute confidence intervals: by default, confidence intervals are not computed for any AUs. When selected, confidence intervals will be computed, providing they are also chosen for the component VUs (and are consistent across the VUs); and
- Verification units are statistically dependent in space: when computing confidence intervals, the stationary block bootstrap can account for spatial dependence between the component VUs by fixing (in absolute time) the sampled block of pairs across the component VUs, i.e. by sampling within the same window for the component VUs. Otherwise (by default), no spatial dependence is assumed, and the bootstrap samples are derived separately for each VU.

Fig. 11: advanced aggregation options



Options for HMOS.Streamflow

☑ Pool pairs (will ignore weight parameters).

☑ Compute confidence intervals (if bootstrap set for component units).

☑ Verification units are statistically dependent in space (for confidence intervals).

5.5 The Output window

The Output window of the EVS allows for plotting of the verification results from one or more VUs or AUs. The units available for plotting are shown in the top left table, with VUs colored blue and AUs colored red (see Fig. 4). On selecting a particular unit under “1a. Select unit(s) with results”, a list of metrics with available results appears in the right-hand table, “1b. Choose products for selected unit.” On selecting a particular metric, the bottom left table, “1c. Choose lead times for selected product”, displays a list of lead times (in hours) for which the metric results are available.

When verifying or aggregating the paired data, the sample from which verification metrics are computed is generated by pooling pairs from equivalent lead times. Products may be generated for some or all of these lead times, and will vary with the metric selected. For example, in selecting ten lead times for the modified box plot, it is possible to produce one graphic with ten boxes showing the (pooled) errors across those ten lead times. In contrast, for the reliability diagram, one graphic is produced for each lead time, with reliability curves for all thresholds specified in each graphic. The units, products, and lead times and are selected by checking the adjacent boxes in the last column of each table. In addition, when the product and lead time tables are populated, right clicking on these tables will provide additional options for selecting multiple products and lead times. The additional options comprise:

Right-click on table “1a. Select unit(s) with results”:

- <u>Select all products for all units:</u> selects all verification metrics at all forecast lead times across all units. This is the “select all” option; and
- <u>Clear selection:</u> this is the “select none” option.

Right-click on table “1b. Choose products for selected unit”:

- <u>Select all times and products:</u> selects all verification metrics and associated forecast lead times for the unit selected in the units table (above);
- <u>Select all times for the highlighted products across all units:</u> selects the highlighted products and associated forecast lead times across all units in the units table (if they exist for other units);

- Select all times for the highlighted products: selects the highlighted products and associated forecast lead times for the unit selected in the units table (multiple rows may be highlighted); and
- Clear selection: clears the selection for the current unit.

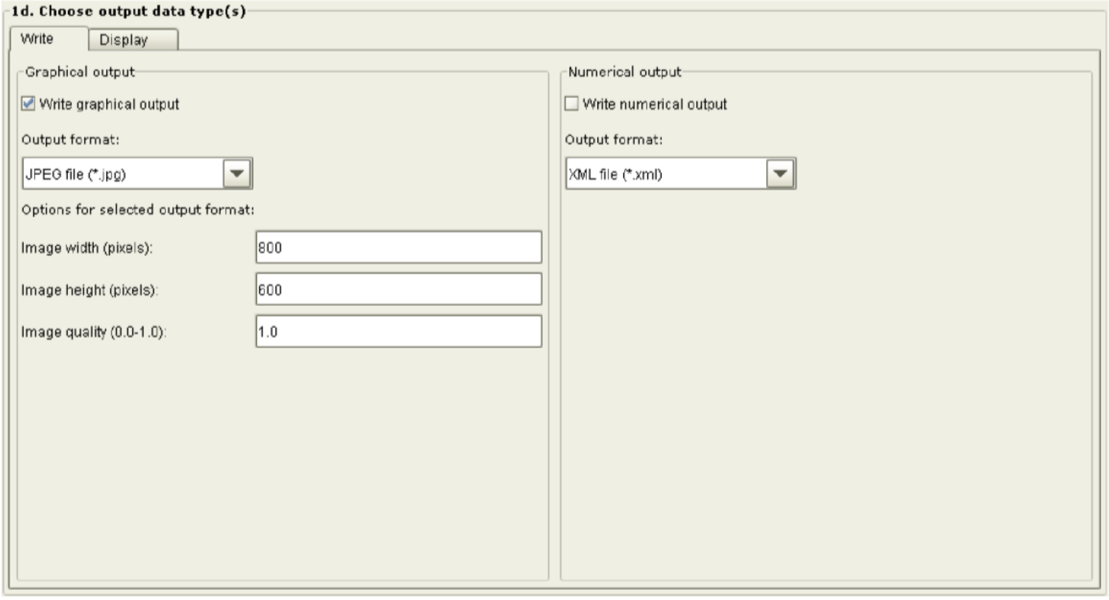
Right-click on the table "1c. Choose lead times for selected product":

- Select all times: selects all forecast lead times for the verification metric selected in the products table (above). If multiple verification metrics are selected in the products table, the lead times will be displayed and selected for the metric that was chosen first, i.e. for the metric at the anchor selection index;
- Select highlighted times: selects the highlighted forecast lead times; and
- Clear selection: clears the selection of forecast lead times.

Products are generated with default options by clicking "**Run**". The default options are to write the numerical results in an XML format and the corresponding graphics in png format to the predefined output folder. The file naming convention is `unit_identifiers.metric_name.lead_time` for plots that comprise a single lead time and `unit_identifiers.metric_name` for the plots that comprise multiple lead times and for the numerical results.

As indicated above, the default output options are defined for each project, and comprise writing of numerical results to an XML file and writing of graphical results to a PNG file. These options are displayed in the bottom right dialog of the main Output window (Fig. 4). Fig. 12a and Fig. 12b show the writing and display options in more detail. The image parameters and formats for writing image files may be modified, and include the PNG and JPEG raster formats and the SVG vector format (which writes much larger files, but maintains line quality with re-scaling). The graphical result may be plotted, edited (re-titled etc.) and saved using an internal viewer, and the numerical results can be shown within the default web-browser. When plotting results for multiple graphics in the internal viewer, a warning is given when more than five graphics will be plotted. A tabbed pane is used to collect plots together for metrics that have one plot for each lead time (Fig. 13). For rapid viewing, these plots may be animated by pressing the "**Animate**" button.

Fig. 12a: product writing options


1d. Choose output data type(s)

Graphical output

☑ Write graphical output

Output format: JPEG file (*.jpg)

Options for selected output format:

Image width (pixels): 800

Image height (pixels): 600

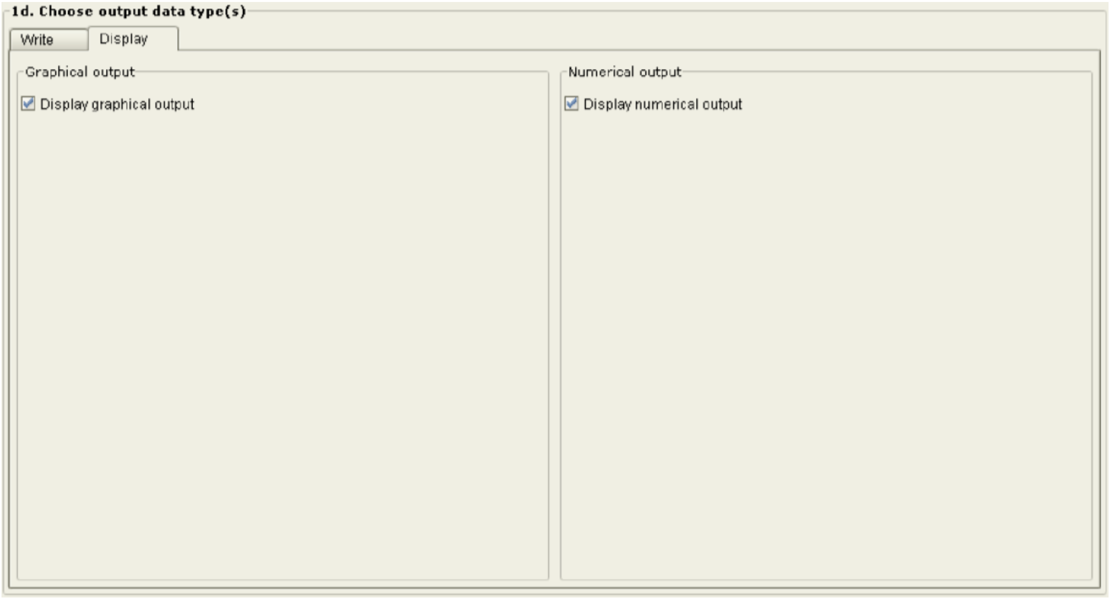
Image quality (0.0-1.0): 1.0

Numerical output

□ Write numerical output

Output format: XML file (*.xml)

Fig. 12b: product display options


1d. Choose output data type(s)

Graphical output

☑ Display graphical output

Numerical output

☑ Display numerical output

When writing numerical outputs for metrics that are based on one or more thresholds of the observations, such as the Brier Score, Relative Operating Characteristic and Reliability diagram, information about these thresholds is written to an XML file with the `_metadata.xml` extension. Specifically, the probability thresholds are written for each time step, together with their values in real units (of the observations) and the numbers of samples selected by those thresholds. An example is given in Fig. 14.

Fig. 13: plot collection for a metric with one plot for each lead time

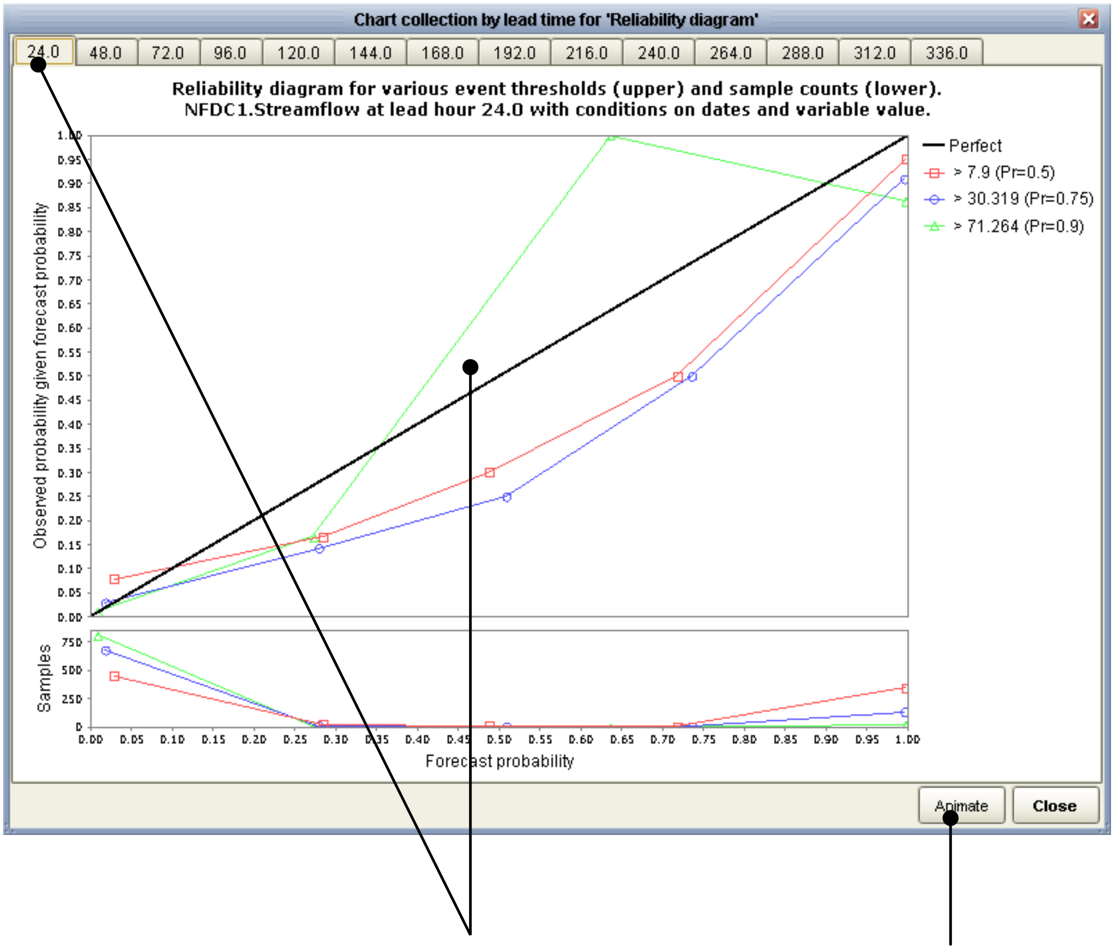


Chart collection by lead time for 'Reliability diagram'

Reliability diagram for various event thresholds (upper) and sample counts (lower).
NFDC1.Streamflow at lead hour 24.0 with conditions on dates and variable value.

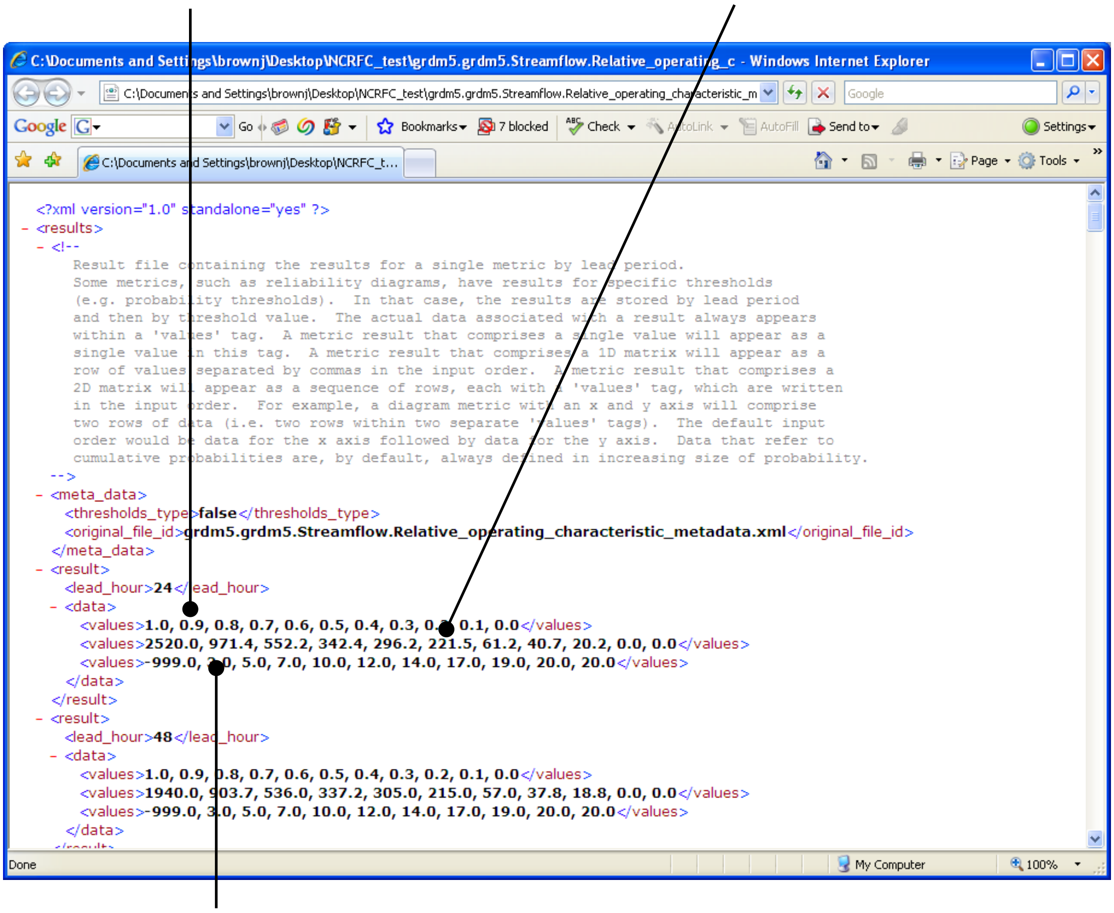
Current lead time (hours)

Animate lead times

Fig. 14: example of a metadata file for metrics based on observed thresholds

Probability thresholds used at first lead time

Real values of thresholds


C:\Documents and Settings\brownj\Desktop\NCRFC_test\grdm5.grdm5.Streamflow.Relative_operating_c - Windows Internet Explorer
C:\Documents and Settings\brownj\Desktop\NCRFC_test\grdm5.grdm5.Streamflow.Relative_operating_characteristic_m
Google
Google
Go
Bookmarks
7 blocked
Check
AutoLink
AutoFill
Send to
Settings
C:\Documents and Settings\brownj\Desktop\NCRFC_t...
Page
Tools
Done
My Computer
100%

```
  <?xml version="1.0" standalone="yes" ?>
- <results>
  - <!--
      Result file containing the results for a single metric by lead period.
      Some metrics, such as reliability diagrams, have results for specific thresholds
      (e.g. probability thresholds).  In that case, the results are stored by lead period
      and then by threshold value.  The actual data associated with a result always appears
      within a 'values' tag.  A metric result that comprises a single value will appear as a
      single value in this tag.  A metric result that comprises a 1D matrix will appear as a
      row of values separated by commas in the input order.  A metric result that comprises a
      2D matrix will appear as a sequence of rows, each with a 'values' tag, which are written
      in the input order.  For example, a diagram metric with an x and y axis will comprise
      two rows of data (i.e. two rows within two separate 'values' tags).  The default input
      order would be data for the x axis followed by data for the y axis.  Data that refer to
      cumulative probabilities are, by default, always defined in increasing size of probability.
    -->
  - <meta_data>
      <thresholds_type>false</thresholds_type>
      <original_file_id>grdm5.grdm5.Streamflow.Relative_operating_characteristic_metadata.xml</original_file_id>
    </meta_data>
  - <result>
      <lead_hour>24</lead_hour>
    - <data>
        <values>1.0, 0.9, 0.8, 0.7, 0.6, 0.5, 0.4, 0.3, 0.2, 0.1, 0.0</values>
        <values>2520.0, 971.4, 552.2, 342.4, 296.2, 221.5, 61.2, 40.7, 20.2, 0.0, 0.0</values>
        <values>-999.0, 3.0, 5.0, 7.0, 10.0, 12.0, 14.0, 17.0, 19.0, 20.0, 20.0</values>
      </data>
    </result>
  - <result>
      <lead_hour>48</lead_hour>
    - <data>
        <values>1.0, 0.9, 0.8, 0.7, 0.6, 0.5, 0.4, 0.3, 0.2, 0.1, 0.0</values>
        <values>1940.0, 903.7, 536.0, 337.2, 305.0, 215.0, 57.0, 37.8, 18.8, 0.0, 0.0</values>
        <values>-999.0, 3.0, 5.0, 7.0, 10.0, 12.0, 14.0, 17.0, 19.0, 20.0, 20.0</values>
      </data>
    </result>
```

Sample counts for each threshold

6. THE VERIFICATION METRICS AVAILABLE IN THE EVS

6.1 Classes of verification metric and attributes of forecast quality

Detailed reviews of ensemble forecast quality can be found in Wilks (2006) and Jolliffe and Stephenson (2003). This section focuses on the verification metrics available in the EVS and the attributes of forecast quality to which they refer. In this context, "attribute" refers to a specific dimension of quality, such as the unbiasedness or "reliability" of the forecast probabilities. Important attributes of forecast quality are obtained by examining the joint probability distribution function (pdf) of the forecasts, *Y*, and observations, *X*, $f_{XY}(x,y)$. The joint distribution can be factored into $f_{X|Y}(x|y)f_Y(y)$, which is known as the "calibration-refinement" factorization or $f_{Y|X}(y|x)f_X(x)$, which is known as the "likelihood-base rate" factorization (Murphy and Winkler, 1987). Differences between $f_X(x)$ and $f_Y(y)$ describe the unconditional biases in the forecast probabilities. The conditional pdf, $f_{X|Y}(x|y)$, describes the conditional reliability of the forecast probabilities when compared to $f_Y(y)$ and "resolution" when only its sensitivity to $f_Y(y)$ is considered. For a given level of reliability, forecasts that contain less uncertainty, i.e. "sharp forecasts", may be preferred over "unsharp" ones, as they contribute less uncertainty to decision making (Gneiting et al., 2007). By way of illustration, a flood forecasting system is "reliable", or conditionally unbiased in its forecast probabilities, if flooding is observed twenty percent of the time when it is forecast with probability 0.2 (repeated for all forecast probabilities). A flood forecasting system has "resolution" if small changes in the forecast probabilities are associated with different observed outcomes, whether or not the forecast probabilities are reliable. In contrast, $f_{Y|X}(y|x)$ measures the ability of the forecasts to "discriminate" between different observed outcomes. An ensemble forecasting system is discriminatory with respect to an event if it consistently forecasts the event's (observed) occurrence with a probability higher than chance (i.e. climatology) and consistently forecasts its (observed) non-occurrence with a probability lower than chance.

In general, the utility of a forecasting system will depend on several attributes of forecast quality (Jolliffe and Stephenson, 2003). However, for a particular application of the forecasts, some attributes of forecast quality may be more important than others. For example, when issuing flood warnings, it is particularly important that observed flood flows and non-flood flows are discriminated between, because flood warnings are only effective if they are consistently correct and do not “cry wolf”.

For any given attribute of forecast quality, there are several possible metrics or measures of quality. For example, summary statistics for reliability and resolution can be obtained from quadratic error statistics, such as the BS (Brier, 1950), which contains a summed contribution from these two components (Murphy, 1996). When more details are required, specific events may be defined, such as flooding or the occurrence of precipitation, and forecast quality determined over specific ranges of forecast probability (as in the reliability diagram; Hsu and Murphy, 1986). Only those metrics thought to convey significantly different aspects of forecast quality are included in the EVS, which includes metrics that convey specific attributes of quality at various levels of detail (see Table 4). The flexibility to consider different attributes of forecast quality at various levels of detail is important, as the EVS is intended for a wide range of applications and users.

The EVS includes single-valued error statistics, which can be used to verify the ensemble average forecast, and statistics that measure the quality of the forecast probabilities. While single-valued metrics cannot verify the forecast probabilities, they are useful for comparing deterministic forecasts with the “best estimate” from the ensemble forecast (such as the ensemble mean), particularly if the ensemble forecasts were derived from single-valued forecasts (e.g. via Model Output Statistics; Gneiting et al., 2005). However, caution should be exercised when using single-valued measures to verify the ensemble mean forecast, because the ensemble spread adds potential skill to the ensemble forecast and is not verified by a single-valued measure. Currently, the single-valued measures available in the EVS include the mean error, the mean absolute error, the RMSE, and the coefficient of correlation between the ensemble average forecast and the observed outcome (Table 4). Table 4 lists the verification metrics that are currently available in the EVS, which contain varying levels of detail about the forecasting errors. The verification scores, such as the BS and the Continuous Ranked Probability Score (CRPS) are integral measures of forecast quality and are less sensitive to sampling uncertainty. Sampling uncertainty is an important concern when verifying forecast probabilities (Jolliffe and Stephenson, 2003; Wilks, 2006), particularly for extreme events (Bradley et al., 2003). Also, the BS and CRPS may be decomposed into summed contributions from (lack of) reliability and resolution (Murphy 1996, Hersbach 2000).

As indicated above, reliability and discrimination are two key attributes of ensemble forecast quality. Both unconditional and conditional biases contribute to a lack of reliability in the forecast probabilities. If the forecasting system is conditionally unbiased, it is also unconditionally unbiased, but the reverse may not hold. The conditional biases are often considered alongside the forecast spread or “sharpness”, because sharp forecasts are more informative, but not necessarily more reliable (Gneiting et al., 2007). For example, a forecast that issues the climatological probability of an event is unconditionally unbiased, because the average observed and forecast probabilities are, by definition, the same. However, it is conditionally biased, because hydrologic events are conditional upon several factors, such as precipitation amount and antecedent soil conditions. The conditional bias corresponds to the difference between a forecast issued from a perfectly reliable forecasting system (the diagonal line in the reliability diagram; Hsu and Murphy, 1986) and the climatological probability of occurrence (a horizontal line in the reliability diagram). Several metrics are available in the EVS for assessing the unconditional and conditional biases that contribute to unreliable forecast probabilities. In order of increasing detail, these include; 1) the reliability component of the mean CRPS ($\overline{CRPS}$; Matheson and Winkler, 1976; Hersbach, 2000); 2) a plot of the unconditional biases in the forecast probabilities (the mean error of probability diagram, MEPD); 3) a plot of the conditional biases in the forecast probabilities (the spread-bias diagram, SBD), which that is similar to the cumulative rank histogram (Anderson, 1996; Hamill, 1997; Talagrand, 1997); and 4) the reliability diagram, which plots the conditional biases in the forecast probabilities of a discrete event, such as flooding, and includes a plot of sharpness (Hsu and Murphy, 1986).

The reliability component of the $\overline{CRPS}$ measures the average reliability of the ensemble forecasts across all possible events (Hersbach, 2000). Specifically, it shows whether the observed outcome falls below the *j*th of *m* ranked ensemble members, $\{z_{j-1} \leq z_j; j=2,\ldots,m\}$, in proportion to *j/m*, on average. The MEPD shows the frequency with which an observed outcome falls below a probability threshold in the unconditional or “climatological” forecast distribution (Section 6.2). The SBD is closely related to the reliability component of the $\overline{CRPS}$. It shows the frequency with which an observed outcome falls below a probability threshold in the (conditional) forecast distribution (see Section 6.2). The MEPD, the SBD, and the reliability diagram all measure bias in probability and have a common graphical interpretation. In each case, a deviation from the diagonal line represents to a lack of calibration in the forecast probabilities, whether unconditional (the MEPD) or conditional upon the forecast ensemble (the SBD) or specific forecast events (the reliability diagram). The reliability diagram plots the conditional probability that an event is observed to occur, *given the forecast*, against its forecast probability of occurrence (Hsu and Murphy, 1986; Bröcker and Smith, 2007a). It is useful to distinguish between the unconditional and conditional biases in the forecast probabilities, because the unconditional biases are more easily removed (e.g. through post-processing; Hashino et al., 2006), and may originate from different sources.

One measure of resolution and two measures of discrimination are currently available in the EVS, namely: 1) the resolution component of the $\overline{CRPS}$ (Hersbach, 2000); 2) the Relative Operating Characteristic (ROC) score (Mason and Graham, 2002; Fawcett, 2006); and; 3) the ROC curve (Green and Swets, 1966; Mason and Graham, 2002). The resolution component of the $\overline{CRPS}$ measures the average ability of the forecasts to distinguish between different observed outcomes, whether or not they were forecast reliably (Hersbach, 2000). The forecasting system has positive resolution if it performs better than the climatological probability forecast. The ROC score and ROC curve measure the ability of the forecasts to discriminate between observed events and non-events, such as flooding versus no flooding. In this context, there is a trade-off between the correct prediction of occurrences and the correct prediction of non-occurrences, or the probability level at which actions are triggered. For example, if a flood warning is triggered by only a small probability of flooding, there is a smaller chance that a flood event will evade detection, but there is a concomitantly higher chance that a non-event will be forecast incorrectly (i.e. of “crying wolf”; other factors being equal). Thus, the ROC curve plots the probability of detection against the probability of false detection for a range of forecast probability levels (Green and Swets, 1966). The ROC score measures the average gain over climatology for all probability levels (based on the integral of the ROC curve).

In addition to measures of reliability and discrimination, there are several composite measures of forecasting error provided in the EVS. In order of increasing information content, these include: 1) the BS; 2) the $\overline{CRPS}$; 3) the Mean Capture Rate Diagram (MCRD); and 4) box plots of errors in the forecast ensemble members. The BS and the $\overline{CRPS}$ quantify the mean square error of the forecast probabilities for a single threshold and for all thresholds, respectively. In contrast, the MCRD and box plots show the forecasting errors in linear units (see Section 6.2). The quadratic form of the BS and the $\overline{CRPS}$ allows for their decomposition into reliability, resolution, and uncertainty (Murphy, 1996). However, this also complicates their use in operational forecasting, where low-probability, high-impact, events are crucial, but the square errors of probability in the forecasts are necessarily small (see Section 6.2 also). In order to support comparisons between forecasting systems and across hydroclimatic regimes, the Brier Skill Score (BSS) and the Continuous Ranked Probability Skill Score (CRPSS) are also provided in the EVS. In both cases, the reference forecast is user-defined, and is introduced by defining an additional VU in the EVS.

6.2 Metrics developed for the EVS with an emphasis on operational forecasting

In addition to the standard metrics for reliability, resolution and discrimination, the EVS provides a platform for testing new metrics. Currently, these include the mean error of probability diagram (MEPD), which measures the unconditional biases in the forecast probabilities, the spread-bias diagram (SBD), which is similar to the (cumulative) rank histogram and tests the forecasts for conditional reliability (Anderson, 1996; Hamill, 1997; Talagrand, 1997), the Mean Capture Rate Diagram (MCRD), which is based on the Probability Score of Wilson et al. (1999), and modified box plots of the ensemble forecast errors versus observed amount. An important aim in developing these metrics was to provide operational forecasters with more application-oriented measures of ensemble forecast quality.

The MEPD measures the reliability of an ensemble forecasting system in an unconditional sense. Let z_{ij} denote the jth of m ensemble members from the ith of n ensemble forecasts and let x_i^o denote the observed outcome associated with the ith ensemble forecast. The forecast climatology has an empirical distribution function, $\hat{F}_{nm}(v)$, which is computed from the n ensemble forecasts as

$$\hat{F}_{nm}(v) = {}^{1}\!/_{n}\sum_{i=1}^{n}\hat{F}_{m_i}(v) \quad where \quad \hat{F}_{m_i}(v) = {}^{1}\!/_{m}\sum_{j=1}^{m}\mathbf{1}\{z_{ij} \le v\}, \qquad (1)$$

and $\mathbf{1}\{\cdot\}$ is a step function that assumes value 1 if the condition is met and 0 otherwise. Let $H = [a,b \,|\, a,b \in [0,1]]$ denote an interval of fixed width on the support of $\hat{F}_{nm}(v)$. The MEPD counts the fraction of observations that fall within the interval, H, namely

$$MEPD(H) = \frac{1}{n}\sum_{i=1}^{n}\mathbb{1}\{\hat{F}_{nm}(x_i^o) \in H\}. \tag{2}$$

An ensemble forecasting system is unconditionally reliable or marginally calibrated over the interval, *H*, if it captures observations in proportion to the width of that interval

$$\lim_{n,m\to\infty}\left\{\frac{1}{n}\sum_{i=1}^{n}\mathbb{1}\{\hat{F}_{nm}(x_i^o) \in H\}\right\} = b - a. \tag{3}$$

The MEPD shows $MEPD(H)$ against the width of *H* for each of *k* windows that span the unit interval. In practice, the *k* windows may cover any subintervals of the unit interval. The MEPD is similar to the quantile-quantile (Q-Q) plot (Wilks, 2006) and the probability-probability (P-P) plot (Shorack and Wellner, 1986; Gneiting et al., 2007). The Q-Q plot compares the order statistics of two samples, or the order statistics of one sample against the values of a theoretical distribution at corresponding quantiles (Wilks, 2006). The P-P plot compares the quantiles corresponding to these order statistics. Indeed, the MEPD is equivalent to a P-P plot of the climatological distributions of *X* and *Y* when evaluated for the *n* intervals, $\left\{H_j = [0,b_j] \,|\, b_j = \frac{j}{n+1}, j = 1,...,n\right\}$. As indicated above, the MEPD assumes asymptotic convergence of $MEPD(H)$ as *n*→∞. In practice, this may be evaluated by comparing the $MEPD(H)$ for *g* subsamples of the *n* available data.

For continuous random variables, such as temperature and streamflow, the SBD provides a simple measure of conditional reliability. It involves counting the fraction of observations, $SBD(I)$, that fall within an interval of fixed width on the support of the *i*th forecast, $I = [c,d \,|\, c,d \in [0,1]]$

$$SBD(I) = \frac{1}{n}\sum_{i=1}^{n}\mathbb{1}\{\hat{F}_{m_i}(x_i^o) \in I\}. \tag{4}$$

An ensemble forecasting system is reliable over the interval, *I*, if it captures observations in proportion to the width of that interval

$$\lim_{n,m\to\infty}\left\{\frac{1}{n}\sum_{i=1}^{n}\mathbb{1}\{\hat{F}_{m_i}(x_i^o) \in I\}\right\} = d - c. \tag{5}$$

By defining *k* windows on the unit interval, $\left\{ I_j = [c_j, d_j] \mid c_j, d_j \in [0,1];\, j = 1,...,k \right\}$, the reliability can be determined for the entire range of forecast probabilities. In practice, the *k* windows may cover any subintervals of the unit interval. Certain windows may be preferred for some applications or for sampling reasons. For example, if the forecasts are uncertain in the tails, windows centered on the forecast median may be preferred. The SBD shows the observed frequency, $SBD(I)$, against the expected frequency, *d-c*. Any deviation from the diagonal line represents a lack of reliability in the forecast probabilities. More specifically, the ensemble forecasts are unreliable if the observed frequency, $SBD(I)$, deviates from the expected frequency by more than the sampling uncertainty of $SBD(I)$. If the *k* windows each cover a probability interval of *1/k*, the expected frequency has a uniform probability distribution, and the actual reliability can be tested for its goodness-of-fit to a uniform distribution (e.g. using the one-sided Cramer von Mises test; Anderson, 1962; Elmore, 2005; Bröcker, 2008).

For continuous random variables, the expected $SBD(I)$ is equal to the width of the interval, *I*, and is, therefore, strictly increasing as the width increases (see above). However, for mixed random variables, such as precipitation and wind-speed, the discrete portion of the probability distribution comprises an infinite number of intervals of different width. Although the window definition could be adapted for this case (see Hamill and Colucci, 1997 for a similar discussion), the reliability diagram may be preferred for mixed random variables.

While the SBD is analogous to the cumulative rank histogram, it explicitly defines the width of the interval, *I*, into which observations fall. When these windows are based on non-exceedence probabilities and are uniform in width (as well as non-overlapping and exhaustive), the SBD is also analogous to the Probability Integral Transform (PIT) (Casella and Berger, 1990), although the latter involves fitting a parametric cdf to the ensemble forecast distribution prior to evaluating the PIT (Gneiting et al., 2005). In that case, the SBD, the cumulative rank histogram and the PIT can also be summarized with the reliability component of the $\overline{CRPS}$ (Hersbach, 2000), which tests whether an observation falls below a threshold with a frequency proportional to the cumulative probability of that threshold (averaged across all thresholds).

Integral measures of forecasting error are widely used in ensemble verification and include the BS and CRPS. As indicated above, the BS and CRPS may be decomposed into a reliability component, a resolution component, and an uncertainty component (Hersbach, 2000). In addition, they have the important property of being "strictly proper" (Bröcker and Smith, 2007b; Gneiting et al., 2007). A scoring rule is "proper" if it is maximized for a forecaster's true belief and is "strictly proper" if its maximum is unique (Gneiting et al., 2007). While linear scores are improper, quadratic scores, such as the BS and CRPS, are strictly proper. Nevertheless, if the user has a strong risk aversion towards extreme events, quadratic scores may not be desirable. The Probability Score (PS) of Wilson et al. (1999) is not strictly proper but has some appeal in operational forecasting (see also, Mason, 2008). The PS integrates the forecast probability distribution, $f_Y(y)$, over a symmetric window of width, *w*, around the observed outcome, x^o, and is defined as $PS(f_Y, x^o, w)$

$$PS(f_Y, x^o, w) = \int_{x^o - 0.5w}^{x^o + 0.5w} f_Y(y)dy. \tag{6}$$

As with the $\overline{CRPS}$, the $PS(f_Y, x^o, w)$ is averaged over *n* pairs of forecasts and verifying observations to form the $\overline{PS}(w)$

$$\overline{PS}(w) = {}^{1}\!/\!_{n} \sum_{i=1}^{n} PS(f_{Y_i}, x_i^o, w). \tag{7}$$

On average, the probability that a forecast value (or ensemble member) will fall within *w* of the observed value is $\overline{PS}(w)$. The expected PS of a perfect forecasting system is 1, because any given window around x^o will fully capture $f_Y(y)$. The $\overline{PS}(w)$ may be separated into an unconditional bias term, $\overline{PS_U}(w)$, and a conditional bias term, $\overline{PS_C}(w)$, where $\overline{PS}(w) = \overline{PS_U}(w) + \overline{PS_C}(w)$. The $\overline{PS_U}(w)$stems from a lack of reliability in the forecast climatology, $\overline{f_Y}$, relative to the observed climatology, $\overline{f_X}$, and is given by the absolute difference in the $\overline{PS}(w)$ for the forecasts $\overline{f_Y}$ and $\overline{f_X}$, i.e. $\overline{PS_U}(w) = \left| {}^{1}\!/\!_{n} \sum_{i=1}^{n} PS(\overline{f_{Y_i}}, x_i^o, w) - {}^{1}\!/\!_{n} \sum_{i=1}^{n} PS(\overline{f_{X_i}}, x_i^o, w) \right|$. The conditional bias may be deduced from $\overline{PS_C}(w) = \overline{PS}(w) - \overline{PS_U}(w)$.

When basing decisions on the $\overline{PS(w)}$, *w* may be interpreted as a “significant operating error”. For example, when forecasting dam inflows, a high probability of realizing an error greater than *w* (i.e. 1-$\overline{PS(w)}$), on average, may have some practical implications for regulating dam outflows. In other cases, there may be no single *w* on which to base decisions. The Mean Capture Rate Diagram (MCRD) plots 1-$\overline{PS(w)}$ for all possible *w*. The integral of the MCRD for the perfect forecasting system is 0, since *E*[*1-PS*]=*0* for all real values of *w*. While the PS is not strictly proper, there is an analytical relationship between the integral of the MCRD, denoted IPS, where $IPS = \int\int_{x^o-0.5w}^{x^o+0.5w} f_Y(y)dy\,dw$, and the strictly proper CRPS

$$IPS = CRPS + 2E[X \cdot F_Y(y)] - E[X]. \tag{8}$$

Thus, the integral of the MCRD is directly related to the $\overline{CRPS}$. However, of greater practical significance, the IPS is more sensitive to errors in the tails of the forecast probability distribution than the $\overline{CRPS}$.

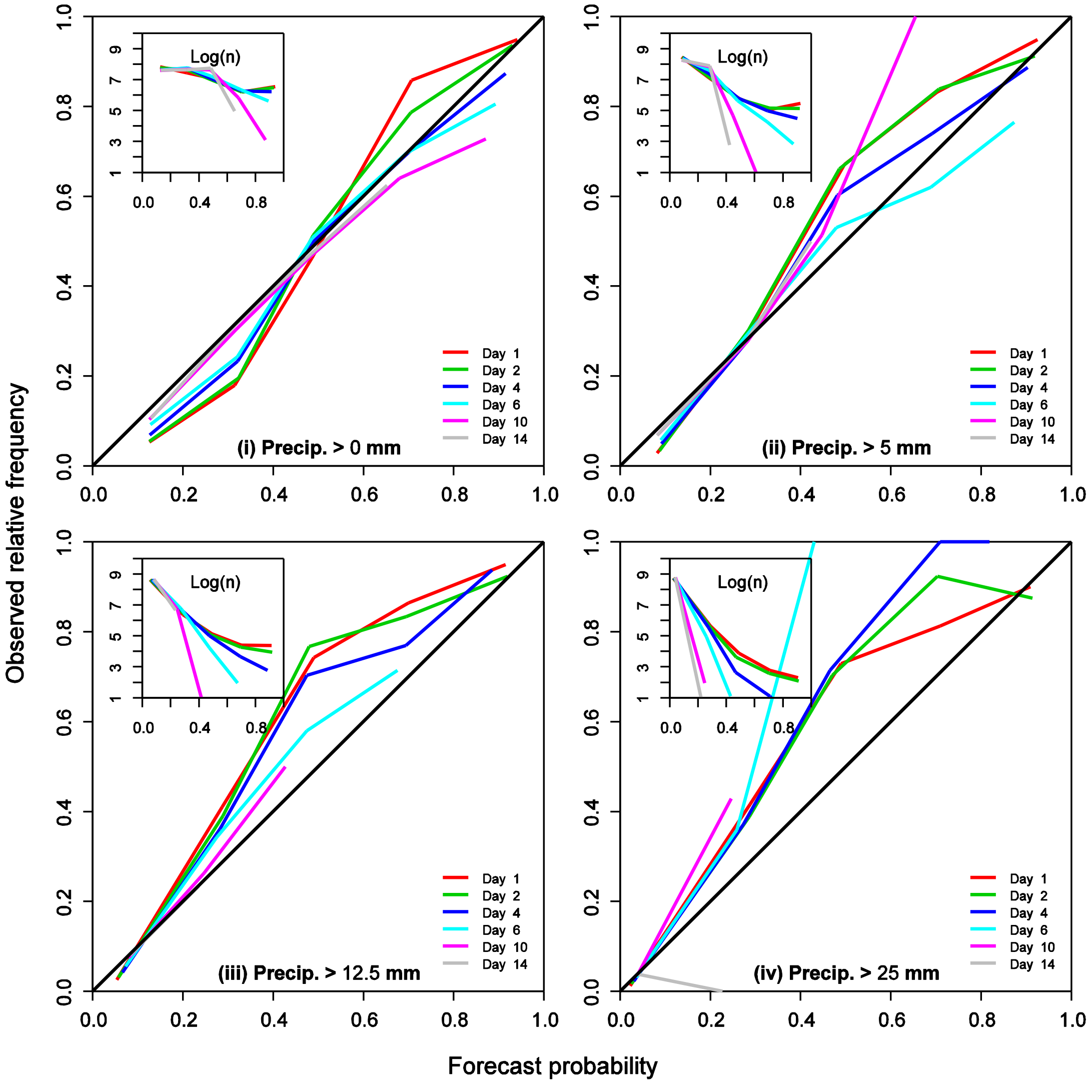
7. EXAMPLE APPLICATIONS OF THE EVS

7.1 Precipitation forecasts from the NWS Ensemble Pre-Processor (EPP)

Six-hourly mean areal precipitation (MAP) totals were hindcast for a 17 year period between 1 January 1979 and 31 December 1996 for the North Fork of the American River above the North Fork Dam (USGS stream gauge station 11427000, NWS forecast point NFDC1), near Sacramento, California. The hindcasts were produced with the NWS Ensemble Pre-Processor (EPP; Schaake et al., 2007) for two MAP areas that contribute to streamflow at NFDC1. The EPP uses a form of Model Output Statistics (MOS) to generate ensemble forecasts of precipitation from single-valued forecasts. The technique is based on a linear regression of the single-valued forecasts and observations in normal probability space. Ensemble traces are then sampled from the conditional probability distribution of the observations, given the single-valued precipitation forecast (Schaake et al., 2007). When sampling from the conditional probability distribution at different lead times, the temporal correlations are reconstructed approximately using the Schaake Shuffle technique (Clark et al., 2003). In the current application, the single-valued forecasts were obtained from the frozen version of the Global Forecast System (GFS; frozen circa 1998) of the National Centers for Environmental Prediction (NCEP) and comprise the ensemble mean of the GFS forecasts (Toth et al., 1997; Hamill et al., 2006; Schaake et al. 2007; Wei et al., 2008). The GFS-EPP precipitation ensembles comprise a continuous record of six-hourly forecasts, with lead times ranging from 6 to 336 hours in six-hourly increments. Each GFS-EPP forecast contains 40 ensemble members, and each member represents an equally likely prediction of the total precipitation within the six-hour period. Using the EVS, the forecasts were aggregated from six-hourly totals to daily totals, and the verification statistics were averaged across the two MAP areas.

Fig. 15 shows the reliability of the GFS-EPP forecasts for daily precipitation totals exceeding 0.0 (i.e. probability of precipitation, PoP), 5.0, 12.5, and 25 mm at lead times of 1, 2, 4, 6, 10 and 14 days. The sampling uncertainties were too large to evaluate forecast reliability at thresholds exceeding 25 mm. As indicated in Fig. 15, the forecast probabilities are reliable for PoP and low precipitation amounts (e.g. >5.0 mm), particularly at lead times of 4 and 6 days, and are reasonably reliable for other precipitation amounts. At moderate (>12.5 mm) and high (>25 mm) precipitation thresholds, there is a tendency for the forecast probabilities to fall below the observed relative frequencies. This is associated with a low-bias in the ensemble mean forecast for large precipitation amounts (see the upper-right plot in Fig. 17, together with Fig. 18). Also, as the event thresholds and lead times increase, the number of forecasts issued with high probability, i.e. the "sharpness", declines rapidly.

Fig. 15: Reliability diagrams for the EPP precipitation forecasts



ROC measures the ability of an ensemble forecasting system to discriminate predefined events, such as the occurrence versus non-occurrence of precipitation, and is insensitive to reliability. The ROC curves in Fig. 16 show the Probability of Detection (POD) versus the Probability of False Detection (POFD) for varying probability levels of the GFS-EPP forecasts. Here, an event is defined for daily precipitation totals exceeding 0.0, 5.0, 12.5 or 25 mm at lead times of 1, 2, 4, 6, 10 or 14 days. The POD and POFD are plotted for twelve, equally spaced, probability thresholds. The diagonal line in each plot represents the climatological probability forecast or “zero skill” line. At short lead times, the ensemble forecasts are much more skillful than the climatological probability forecast across all precipitation amounts. Notably, while the ROC area declines consistently with forecast lead time, it increases slightly with precipitation threshold at lead times of 1 and 2 days. This is contrary to the expectation that forecast skill declines with increasing precipitation amount. However, NFDC1 lies on the upslope of the Sierra Nevada mountain range, where significant precipitation events are often enhanced by orographic lifting and are, therefore, relatively predictable at short lead times.

Fig. 16: Empirical ROC curves for the EPP precipitation forecasts

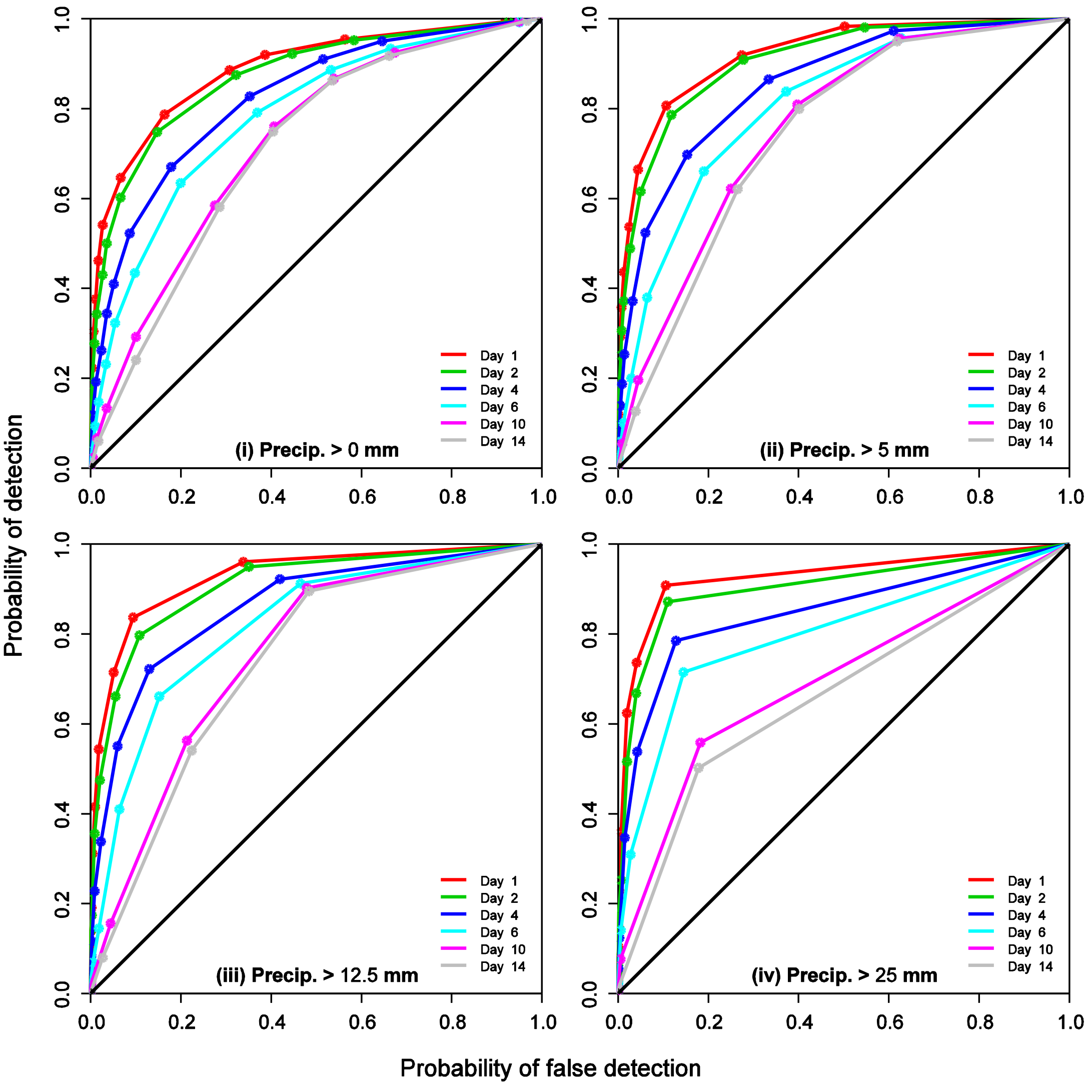


Fig. 17: Deterministic error statistics and $\overline{CRPS}$ for the EPP precipitation forecasts

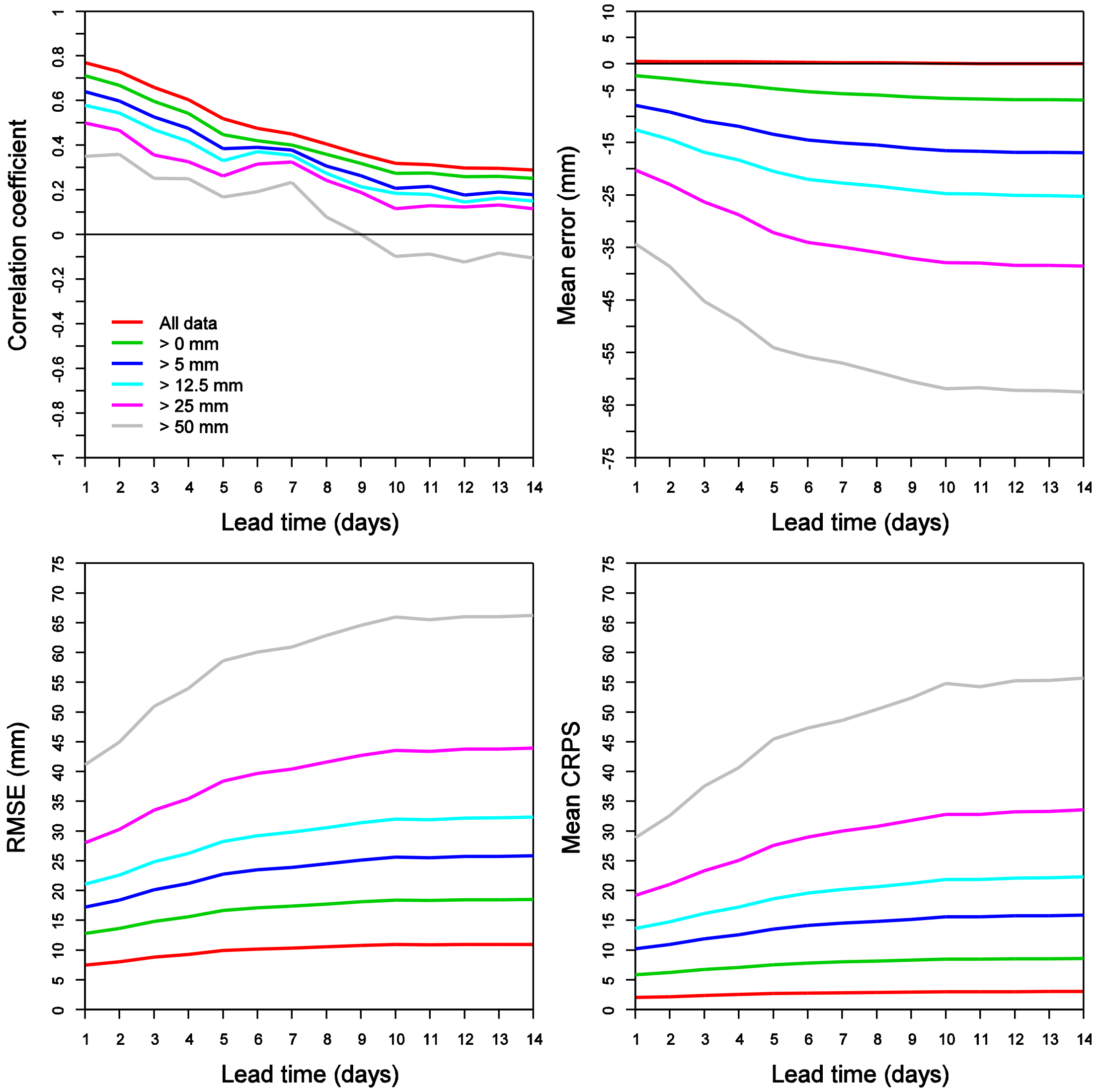
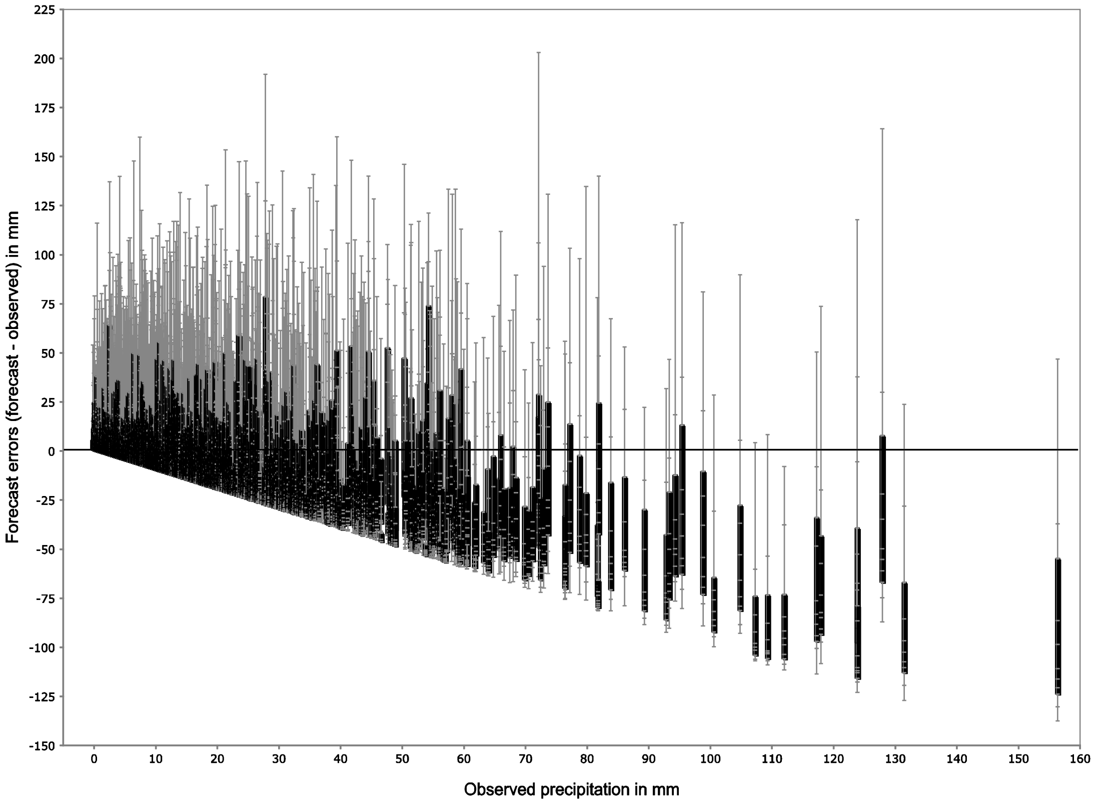


Fig. 17 shows the quality of the ensemble mean forecast in terms of mean error, RMSE and correlation with the observed amount, together with the $\overline{CRPS}$, which provides a lumped measure of error in the forecast probabilities. The statistics were computed for all forecast-observation pairs and for subsets whose observed values exceeded a threshold. As indicated in Fig. 17, there is a progressive decline in forecast quality with increasing lead time and observed precipitation amount, both in terms of the ensemble mean forecast (correlation coefficient, mean error, RMSE) and the overall forecast probabilities ($\overline{CRPS}$). The mean error is similar in magnitude to the RMSE, which suggests that much of the forecasting error at high precipitation thresholds stems from a conditional bias in the ensemble mean forecast. This is confirmed in the "modified box plots" of ensemble forecasting errors by observed precipitation amount, which are shown in Fig. 18 for lead day 1. Here, the forecasting errors (ensemble member – observed value) are plotted with box-and-whisker diagrams, where the whiskers are drawn at quantiles of the forecast error distribution (deciles in this case) and the middle quantiles are shaded (the middle six deciles in this case). The-box-and-whisker diagrams are then arranged by observed value in ascending order. The conditional bias in the ensemble mean forecast is readily apparent in Fig. 18, and shows over-forecasting of low precipitation amounts and under-forecasting of high amounts.

Fig. 18: Box plots for the EPP precipitation forecasts on lead day 1



7.2 Streamflow forecasts from the NWS Ensemble Streamflow Prediction system

Mean daily inflows were hindcast for a 17 year period between 1 January 1979 and 31 December 1996 at the North Fork Dam, California (NFDC1). The hindcasts were produced with the NWS Hydrologic Ensemble Hindcaster, which implements part of the NWSRFS in an ensemble framework, known as the Ensemble Streamflow Prediction (ESP) system (Demargne et al., 2007). The NWSRFS was forced with temperature and precipitation ensembles from the GFS-EPP (as described in Section 7.1). The streamflow hindcasts should only be considered illustrative of the EVS and not representative of the operational streamflow forecasts for NFDC1, which are forced with short-range QPF rather than the frozen GFS. These QPFs originate from the NWS Hydrometeorological Prediction Center and may be modified by the RFC forecasters to reflect the real-time streamflow conditions (a form of manual data-assimilation, known as run-time MODs). In general, the modified QPFs are much more skillful than the ensemble means of the frozen GFS. The hindcasts were aggregated from a six-hourly timestep to daily averages for comparison with the observed flows, which were only available as daily averages. The observed flows are based on stage observations, which were converted to flows using measured stage-discharge relations (Kennedy, 1983).

Fig. 19 shows the reliability of the forecasts at selected lead times. The results are shown for flow thresholds corresponding to climatological non-exceedence probabilities of 0.5 (10 $m^3 s^{-1}$), 0.75 (32 $m^3 s^{-1}$), 0.95 (85 $m^3 s^{-1}$) and 0.99 (210 $m^3 s^{-1}$). As indicated in Fig. 19, the forecast probabilities are reliable across a wide range of flow exceedence thresholds and lead times. However, they are slightly overconfident at moderately high flows, as evidenced by the higher forecast probabilities than observed relative frequencies. The forecasts are also consistently less reliable but sharper on lead day 1. This is understandable because the current version of the ESP system ignores uncertainties in the hydrologic model, including those in its initial conditions, structure and parameter values (Seo et al. 2006). Noise in the sharpness and reliability curves for streamflows that were forecast to exceed 210 $m^3 s^{-1}$ with high probability (0.8-1.0) reflects the small sample size and correspondingly high sampling uncertainty for such forecast events. Fig. 20 shows the spread-bias plots for the ESP flow forecasts. These plots show the reliability of the forecast probabilities for all forecast-observation pairs and for subsets of pairs whose observed values exceed a probability threshold in the observed climatological distribution. As indicated in Fig. 20, the forecasts are reasonably reliable across all flow exceedence thresholds and lead times, but tend to underpredict the observed streamflows at the highest flow threshold. Fig. 21 shows the mean error of the ensemble mean forecast, the correlation of the ensemble mean flow with the observed flow, the ROC score, and the mean error of probability diagram (MEPD). While the forecasts are marginally well-calibrated (see the MEPD in Fig. 21), there is a loss of conditional reliability at the highest flow threshold across all forecast lead times (Fig. 19). This conditional bias originates from the conditional bias in the ensemble mean flow (Fig. 21). Overall, the conditional biases in the ESP streamflow forecasts (Fig. 21) are consistent with the conditional biases in the GFS-EPP precipitation forecasts (Fig. 17), which comprise over-forecasting of low precipitation amounts and under-forecasting of high amounts (Fig. 18).

Fig. 19: Reliability diagrams for the ESP forecasts

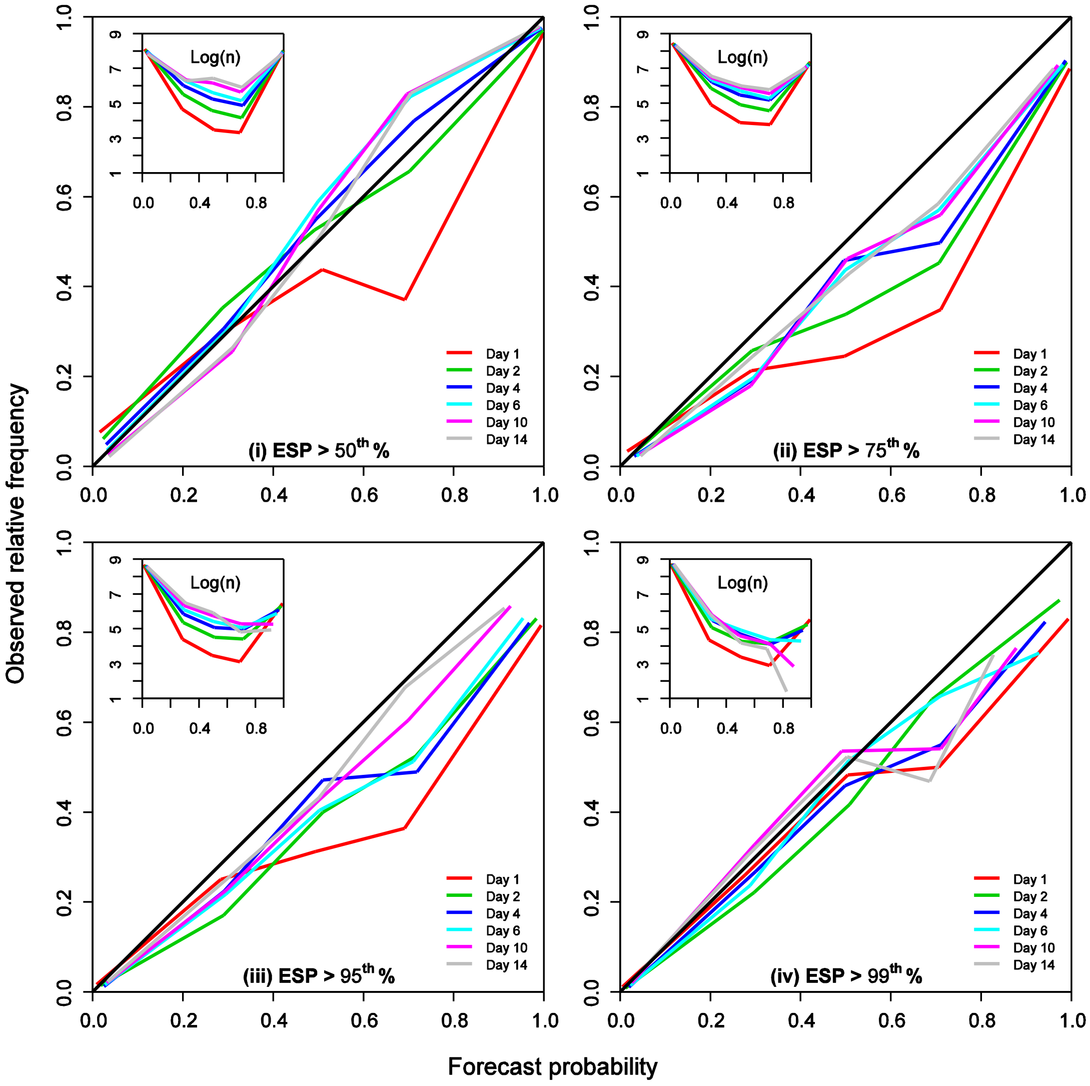


Fig. 20: Spread-bias diagrams for the ESP forecasts

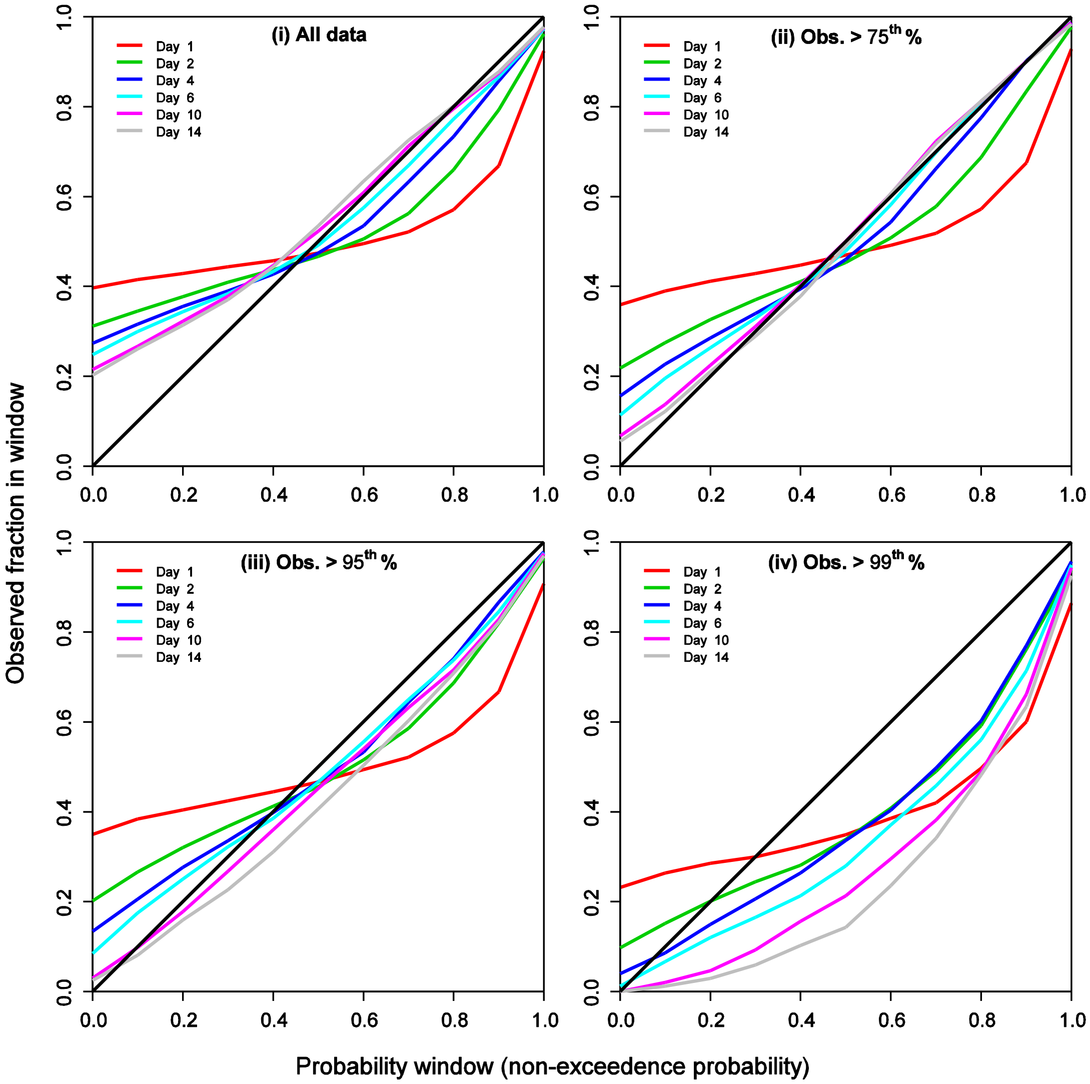


Fig. 21: Deterministic error statistics, ROC score and MEPD for the ESP forecasts

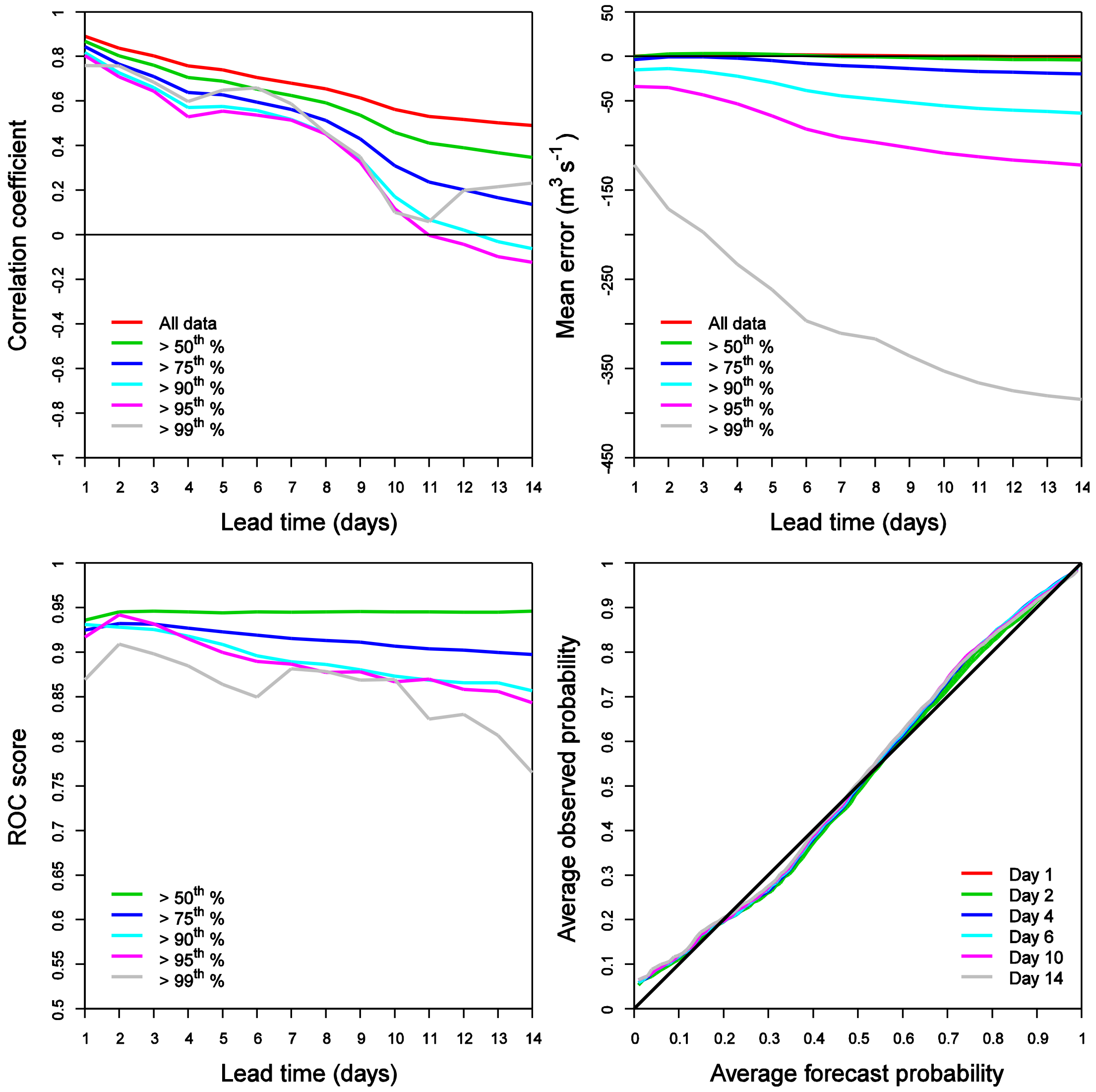


Fig. 22 shows the ROC curves for mean daily flows that correspond to climatological non-exceedence probabilities of 0.5, 0.75, 0.95 and 0.99. In comparison to the precipitation hindcasts, there is more consistent decline in discrimination with increasing forecast lead time and event threshold. Also, the flow forecasts are substantially more skillful than the climatological probability forecast for all forecast lead times and event thresholds. The MCRDs in Fig. 23 show a rapid increase in the mean error of any given ensemble member over lead times of 1 and 2 days and a much slower decline in forecast quality over lead times of 4 to 14 days.

Fig. 22: Empirical ROC curves for the ESP flow forecasts

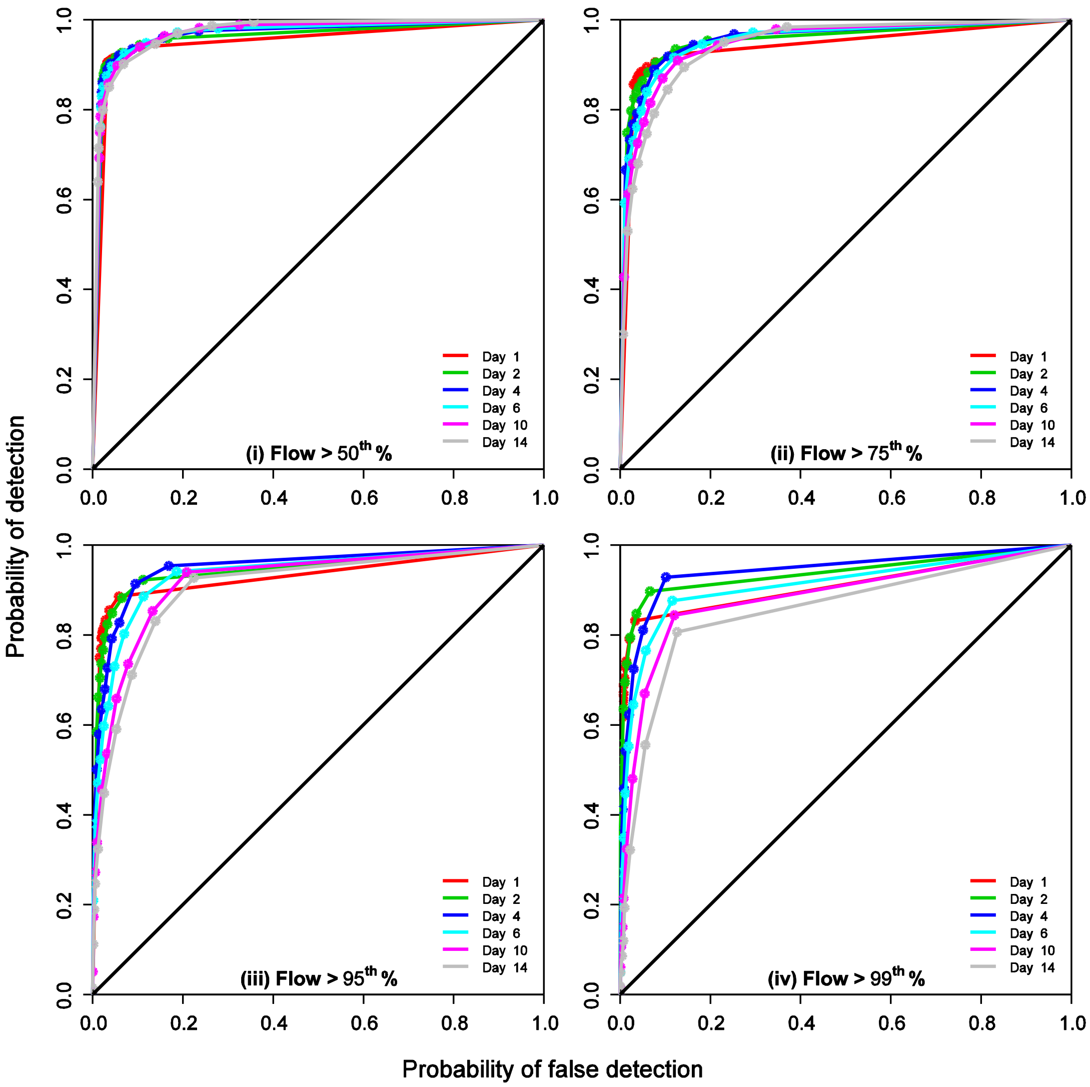
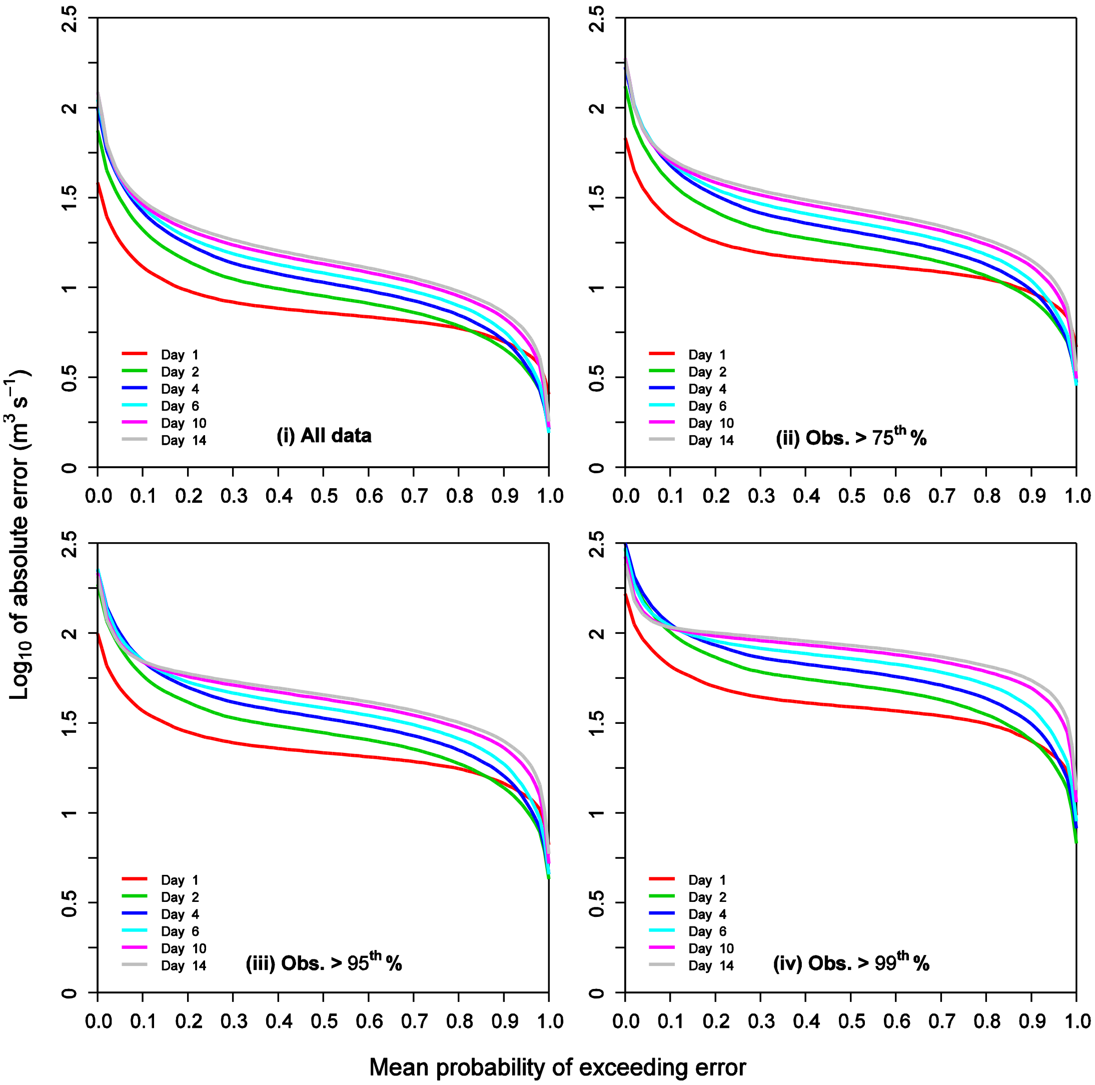


Fig. 23: Mean Capture Rate Diagrams for the ESP flow forecasts



8. THE APPLICATION PROGRAMMERS INTERFACE (API)

8.1 Overview

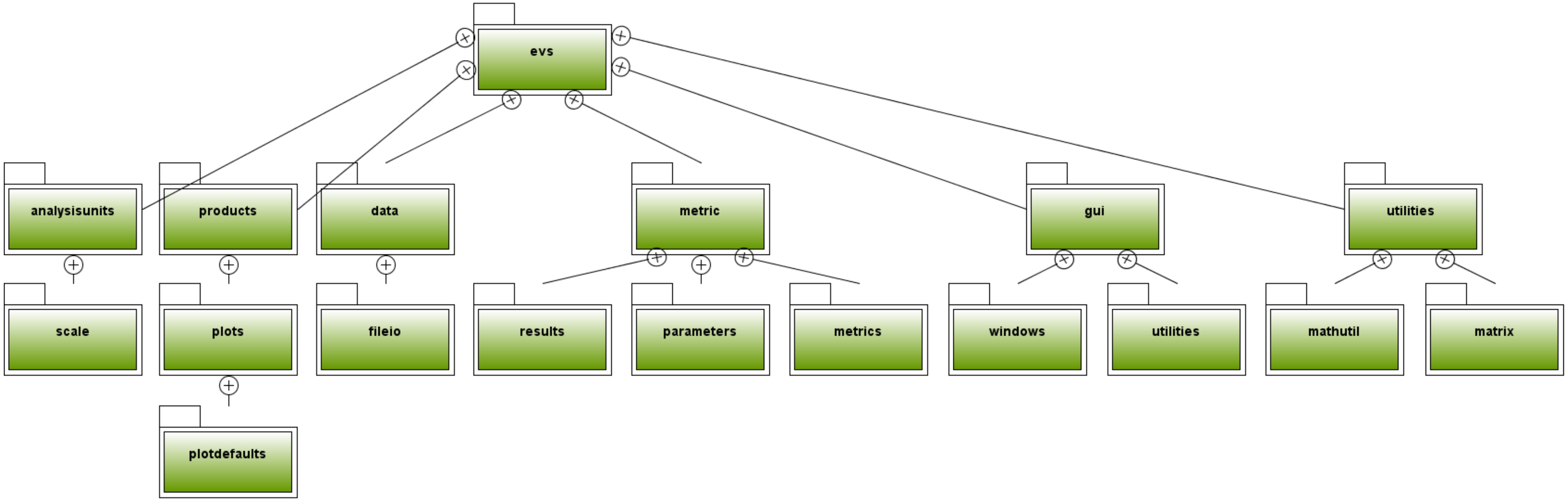
This section provides a brief overview of the API for the EVS and the procedure for adding a new verification metric. Detailed documentation of the code is provided in the hyperlinked html documentation that accompanies the software distribution. Developers may contact the authors for additional information about the source code.

The EVS is written in Java, which is a modern, object-oriented, programming language (Flanagan, 2005). The Java platform comprises the language itself, a library of classes, and a Virtual Machine (VM), which runs on a specific operating system (OS). The VM allows for the “platform-independence” of Java applications. A popular class library and one set of VMs are implemented by Oracle as the Java Runtime Environment (JRE). The EVS requires version 1.7 or higher of the JRE. This is freely available to download from the Java website:

http://www.java.com/en/download/index.jsp

In object-oriented programming, the source code is separated into *classes*, each of which provides the blueprint for a particular *object*. For example, a class that computes the BS for a verification dataset, *a*, at an event threshold, *b*, provides the template for a `BrierScore` object with specific values of *a* and *b*. A class also contains methods, which determine the behavior of an object. For example, the `BrierScore` class contains the method `getThreshold`, which returns the event threshold associated with a particular BrierScore object. Similarities among objects are exploited by linking classes together. This leads to a family tree in which children inherit and extend the functionality of their parents. For example, the `BrierScore` class inherits the functionalities of the `EnsembleMetric`, `ScoreMetric`, and `ThresholdMetric` classes, among others. Groups of classes with related functionalities are stored in packages. For example, the `BrierScore` class is stored in the metrics package. The EVS comprises ~50,000 lines of code, which are separated into in 308 classes and stored in a hierarchy of 26 packages. Fig. 24 shows the main package hierarchy in the EVS. The API is fully documented in hyperlinked HTML, and the code itself is extensively commented (~35,000 lines).

Fig. 24: A UML description of the main packages in the EVS



8.2 Procedure for adding a new metric to the EVS

Due to its modular design, the procedure for adding a new metric to the EVS is tightly structured and requires little code development (beyond that required for the metric calculation). Indeed, much of the code required to implement a new metric in the EVS is dictated by, or already implemented in, a more general class of metric. This is illustrated by adding the logarithmic scoring rule or 'Ignorance Score' to the EVS. The Ignorance Score measures the quality of a probabilistic forecasting system with a numeric score (Good, 1952). A new metric, `IgnoranceScore`, is created in the package `/evs/metric/metrics`. The metric extends the `ScoreMetric` and implements `EnsembleMetric`, `ThresholdMetric`, `DecomposableScore`, `CategoricalMetric`, and `BootstrapableMetric`. In inheriting these classes, several methods must be implemented (for which templates can be found in similar classes, such as the `BrierScore`). For example, in inheriting from `ScoreMetric`, the following methods must be implemented:

- `getID`, returns a unique identifier for the metric;
- `getResultID`, returns an identifier from the list of identifiers in the MetricResult class that indicates the data type of the result;
- `hasRealUnits`, returns true if the metric is defined in units of the observed and forecast variables (e.g. error in mm/day), false otherwise;
- `deepCopy`, returns an independent copy of the metric object. Changes to the parameter values of the copied object are not reflected in the original object; and
- `compute`, computes the metric for each forecast lead time and stores the result.

In order to display the Ignorance Score in the EVS, a default plot must also be created. By adding a class to the `evs/products/plots/defaults` package (e.g. `IgnoranceScorePlot`) and associating the plot with the `IgnoranceScore` class, the Ignorance Score will be plotted in the EVS. The `IgnoranceScorePlot` extends the class `DefaultXYPlotByLeadTime` to plot the Ignorance Score by forecast lead time. A single method, `getDefaultChart`, is then implemented to return an `IgnoranceScorePlot` with the correct y-axis dimension for the Ignorance Score (0-1), and any other information specific to the plotting of this score (e.g. axis and chart titles) [approximately five lines of code]. The plots themselves are created with the `JFreeChart` library (see www.jfree.org/jfreechart/). Once the `IgnoranceScorePlot` is associated with the results from an `IgnoranceScore`, the new metric can be displayed in the Output dialog of the EVS (Section 5.5). Descriptive information about the Ignorance Score can also be displayed in the GUI. This is achieved by setting the `descriptionURL` parameter of the `IgnoranceScore` class (which was inherited from the `Metric` class via `EnsembleMetric`) to the URL of a stable resource with descriptive information. For example, it may point to an html file in the statsexplained package, which contains descriptive information for the other metrics in the EVS.

APPENDIX A1 VERIFICATION STATISTICS COMPUTED IN THE EVS

Table 4 provides a list of the verification metrics supported by the EVS. Below is a short description of each metric, which is also available in the GUI.

Mean error

The mean error (ME) measures the average difference between a set of forecasts and corresponding observations. Here, it measures the average difference between the center of the ensemble forecast (the mean average, by default) and observation.

The ME of the ensemble average forecast, $\overline{\mathrm{Y}}$, given the observation, x, is

$$\mathrm{ME} = {}^{1}\!/_{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} \left(\overline{\mathrm{Y}}_{\mathrm{i}} - \mathrm{x}_{\mathrm{i}} \right). \tag{A1}$$

The ME provides a measure of first-order bias in the forecasts, and may be positive, zero, or negative. A positive mean error denotes overforecasting and a negative mean error denotes underforecasting. A mean error of zero (in the ensemble mean forecast) denotes an absence of bias.

Relative mean error

The relative mean error (RME), or relative bias, measures the mean difference between a set of forecasts and corresponding observations, divided by the mean of the observations. Here, it measures the relative mean difference between the center of the ensemble forecast (the mean average value, by default) and the observations. Given n pairs of forecasts and observations, the RME of the center of the ensemble forecast, $\overline{\mathrm{Y}}$, given the observation, x, is

$$\mathrm{RME} = \frac{\sum_{\mathrm{i}=1}^{\mathrm{n}} \left(\overline{\mathrm{Y}}_{\mathrm{i}} - \mathrm{x}_{\mathrm{i}} \right)}{\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{x}_{\mathrm{i}}}. \tag{A2}$$

The RME provides a measure of relative, first-order, bias in the forecasts, and may be positive, zero, or negative. A positive RME denotes overforecasting and a negative RME denotes underforecasting (assuming that the chosen measure of central tendency should match the observed value, on average). A RME of zero denotes the absence of relative bias in the center of the ensemble forecast.

Mean absolute error

The mean absolute error (MAE) measures the mean absolute difference between a set of forecasts and corresponding observations. Here, it measures the mean absolute difference between the center of the ensemble forecast (the mean average, by default) and the observation.

The MAE of the ensemble mean forecast, $\bar{\mathrm{Y}}$, given the observation, x, is given by

$$\mathrm{MAE} = \tfrac{1}{n}\sum_{i=1}^{n}\left|\bar{\mathrm{Y}}_i - x_i\right|. \tag{A3}$$

The MAE provides a measure of error spread in the center of the forecast distribution. It is similar to the Root Mean Square Error (RMSE), except the RMSE employs square deviations, such that large errors contribution proportionally more to the overall score. The MAE generalizes to the Continuous Ranked Probability Score (CRPS) for ensemble or probability forecasts.

Root mean square error

The mean square error (MSE) measures the average square error of the forecasts. The Root Mean Square Error (RMSE) provides the square root of this value, which has the same units as the forecasts and observations. Here, the forecast corresponds to the ensemble average value (the mean, by default) and an 'error' represents the difference between the ensemble average, $\bar{\mathrm{Y}}$, and the observation, x. The equation for the RMSE is

$$\mathrm{RMSE} = \left[\tfrac{1}{n}\sum_{i=1}^{n}\left(\bar{\mathrm{Y}}_i - x_i\right)^2\right]^{0.5}. \tag{A4}$$

The RMSE provides an indication of the ‘average deviation’ between the forecast value and an observation in real units. The RMSE is either zero, denoting a perfect forecast, or positive.

Correlation coefficient

The correlation coefficient measures the strength of linear association between two variables. Here, it measures the linear relationship between n pairs of ensemble average forecasts and corresponding observations. A correlation coefficient of 1.0 denotes a perfect linear relationship between the forecasts and observations. A correlation coefficient of -1.0 denotes a perfect inverse linear relationship (i.e. the observed values increase when the forecasts values decline and vice versa). The ensemble average forecast may be perfectly correlated with the observations and still contain biases, because the correlation coefficient is normalized by the overall mean of each variable. A correlation coefficient of 0.0 denotes the absence of any linear association between the forecasts and observations. However, a low correlation coefficient may occur in the presence of a strong non-linear relationship, because the correlation coefficient measures linear association only.

EVS computes the Pearson product-moment correlation coefficient, r, which is given by

$$r = \frac{\mathrm{Cov}(x, \bar{Y})}{\mathrm{Std}(x) \cdot \mathrm{Std}(\bar{Y})} , \qquad \text{(A5)}$$

where $\mathrm{Cov}(x, \bar{Y})$ is the sample covariance between the ensemble average forecasts and their corresponding observations. The sample standard deviations of the forecasts and observations are denoted $\mathrm{Std}(\bar{Y})$ and $\mathrm{Std}(x)$, respectively. The sample covariance between the n pairs of forecasts and observations is

$$\mathrm{Cov}(x, \bar{Y}) = \frac{1}{n-1} \sum\nolimits_{i=1}^{n} (x_i - \mu_x)(\bar{Y}_i - \mu_{\bar{Y}}) , \qquad \text{(A6)}$$

where $\mu_{\bar{Y}}$ and μ_x are the overall sample means of the (ensemble average) forecasts and observations, respectively.

Brier Score

The Brier Score (BS) measures the average square error of a probability forecast. It is analogous to the mean square error of a deterministic forecast, but the forecasts, and hence error units, are given in probabilities. The Brier Score measures the error with which a discrete event, such as ‘flooding’, is predicted. For continuous forecasts, such as the amount of water flowing through a river, one or more discrete events must be defined from the continuous forecasts. There are several ways in which an event may be defined, depending on the verification problem. For an event that involves not exceeding some threshold, t, the Brier Score is computed from the forecast probability, $F_Y(t)$, and the corresponding observed outcome, x, whose cumulative probability is 1 if t is exceeded by the observation and 0 otherwise, as defined by the step function, $\mathbf{1}\{\cdot\}$

$$\mathrm{BS}(t) = {}^{1}\!/_{n} \sum_{i=1}^{n} \left(F_{Y_i}(t) - \mathbf{1}\{t \geq x_i\} \right)^2 . \qquad \text{(A7)}$$

A set of forecasts and observations of a binary event match exactly in terms of the BS if the mean square difference in the forecast probability and the corresponding (perfectly sharp) observed probability is zero. Optionally, the BS may be decomposed into contributions due to (lack of) reliability, resolution and uncertainty, namely

$$\mathrm{BS} = \mathrm{reliability} - \mathrm{resolution} + \mathrm{uncerta\,int\,y}. \qquad \text{(A8)}$$

Brier Skill Score

The Brier Skill Score (BSS) measures the performance of one forecasting system relative to another in terms of the Brier Score (BS). The BS measures the average square error of a probability forecast of a dichotomous event. The BSS comprises a ratio of the BS for the forecasting system to be evaluated (the "main forecasting system"), $\mathrm{BS}_{\mathrm{MAIN}}$, over the BS for the reference forecasting system, $\mathrm{BS}_{\mathrm{REF}}$

$$\mathrm{BSS} = 1 - \frac{\mathrm{BS}_{\mathrm{MAIN}}}{\mathrm{BS}_{\mathrm{REF}}} . \qquad \text{(A9)}$$

As a measure of average square error in probability, values for the BS approaching zero are preferred. It follows that a BSS closer to 1 is preferred, as this indicates a low BS of the main forecasting system relative to the BS of the reference forecasting system. Unlike the BS, the BSS is not "strictly proper" (i.e. it can be hedged). Also, the BSS may behave erratically for forecasts of rare events because their errors of probability are necessarily small and their sampling uncertainties are likely high.

Mean Continuous Ranked Probability Score

The Continuous Ranked Probability Score (CRPS) summarizes the quality of a continuous probability forecast with a single number (a score). It measures the integrated square difference between the cumulative distribution function (cdf) of the forecast variable, $F_Y(y)$, and the corresponding cdf of the observed variable, $\mathbf{1}\{y \geq x\}$

$$\mathrm{CRPS} = \int_{-\infty}^{\infty} \left(F_Y(y) - \mathbf{1}\{y \geq x\}\right)^2 dy, \qquad \text{(A10)}$$

where $\mathbf{1}\{y \geq x\}$ is a step function that assumes probability 1.0 for values greater than or equal to the observation, and 0.0 otherwise.

In practice, the CRPS is averaged across n of pairs of forecasts and observations, which leads to the mean CRPS

$$\overline{\mathrm{CRPS}} = \tfrac{1}{n}\sum_{i=1}^{n} \mathrm{CRPS}_i. \qquad \text{(A11)}$$

The numeric value of the mean CRPS will vary with application and is difficult to interpret in absolute terms (e.g. in terms of specific forecast errors). However, the CRPS has some desirable mathematical properties, including its insensitivity to hedging (i.e. the expected value of the score cannot be improved, *a priori*, by adopting a particular forecasting strategy). Other scores, such as the Probability Score of Wilson et al. (1999), may be hedged (in this case by issuing sharper forecasts).

Optionally, the mean CRPS may be decomposed into contributions due to (lack of) reliability, resolution and uncertainty (Hersbach, 2000), namely

$$\overline{\mathrm{CRPS}} = \mathrm{reliability} - \mathrm{resolution} + \mathrm{uncertainty}. \qquad \text{(A12)}$$

Mean Continuous Ranked Probability Skill Score

The mean Continuous Ranked Probability Skill Score ($\overline{\mathrm{CRPSS}}$) measures the performance of one forecasting system relative to another in terms of the mean

Continuous Ranked Probability Score ($\overline{\mathrm{CRPS}}$). The $\overline{\mathrm{CRPS}}$ measures the average square error of a probability forecast across all possible event thresholds. The $\overline{\mathrm{CRPSS}}$ comprises a ratio of the $\overline{\mathrm{CRPS}}$ for the forecasting system to be evaluated (the "main forecasting system"), $\overline{\mathrm{CRPS}}_{\mathrm{MAIN}}$, and the $\overline{\mathrm{CRPS}}$ for a reference forecasting system, $\overline{\mathrm{CRPS}}_{\mathrm{REF}}$

$$\overline{\mathrm{CRPSS}} = \frac{\overline{\mathrm{CRPS}}_{\mathrm{REF}} - \overline{\mathrm{CRPS}}_{\mathrm{MAIN}}}{\overline{\mathrm{CRPS}}_{\mathrm{REF}}}. \tag{A13}$$

As a measure of average square error in probability, values for the $\overline{\mathrm{CRPS}}$ approaching zero are preferred. It follows that a $\overline{\mathrm{CRPSS}}$ closer to 1 is preferred, as this indicates a low $\overline{\mathrm{CRPS}}$ of the main forecasting system relative to the $\overline{\mathrm{CRPS}}$ of the reference forecasting system. Unlike the $\overline{\mathrm{CRPS}}$, the $\overline{\mathrm{CRPSS}}$ is not "strictly proper" (i.e. it can be hedged). Also, the $\overline{\mathrm{CRPSS}}$ may behave erratically for forecasts of rare events because their errors of probability are necessarily small and their sampling uncertainties are likely high.

Mean Capture Rate

A key aspect of forecast quality is the probability of making a given error in real terms. The Probability Score (PS) of Wilson et al. (1999) is useful here because it identifies the probability with which a given, real-valued, error is exceeded. The PS is defined for a symmetric window, w, around the observation, x

$$\mathrm{PS}(w) = \int_{x-0.5w}^{x+0.5w} f_Y(y)\,dy. \tag{A14}$$

It conveys the extent to which an observation is captured by the forecast, where a high probability implies greater forecast performance. The disadvantages of the PS include its subjectivity and sensitivity to hedging, whereby the expected value of the PS is maximized for sharp forecasts.

By averaging the PS over a set of n ensemble forecasts and repeating for all possible windows, w, the probability of exceeding a given acceptable error can be determined and is referred to as the Mean Capture Rate (MCR)

$$\mathrm{MCR}(\mathrm{w}) = {}^{1}\!/_{\mathrm{n}} \sum\nolimits_{\mathrm{i}=1}^{\mathrm{n}} 1 - \mathrm{PS}(\mathrm{w}) \quad \forall \mathrm{w} \in \mathbf{R} \tag{A15}$$

It should be noted that sensitivity to hedging does not apply to the MCR, as it is not a score. The resulting curve may be separated into errors of over-prediction and under-prediction by computing the MCR for ensemble members that exceed the observation and fall below the observation, respectively.

Modified box plots

Box plots (or box-and-whisker diagrams) provide a discrete representation of a continuous empirical probability distribution (Tukey, 1977).

Building on this idea, an empirical probability distribution function (pdf) may be summarized with an arbitrary set of percentile bins of which an arbitrary proportion may be shaded (e.g. the middle 60%), to convey the outer and inner probability densities, respectively. The modified box plots show the forecasting errors (ensemble member – observed value) by forecast lead time. Forecasts with common lead times are pooled before computing the errors and displaying them as a box.

Modified box plots by observed value

Constructs a modified box plot where the errors are plotted against observed value for one forecast lead time. When there are multiple forecasts that have a common observed amount, the errors are pooled across those forecasts.

Modified box plots by forecast value

Constructs a modified box plot where the errors are plotted against forecast value for one forecast lead time. The forecast values are determined by applying a specified function (e.g. mean) to the ensemble members. When there are multiple forecasts that have a common forecast value, the errors are pooled across those forecasts.

Reliability diagram

The reliability diagram measures the accuracy with which a discrete event is forecast by an ensemble or probabilistic forecasting system. The discrete event may be defined in several ways. For example, flooding is a discrete event that involves the exceedence of a flow threshold. According to the reliability diagram, an event should be observed to occur with the same relative frequency as its forecast probability of occurrence over a large number of such forecast-observation pairs. For example, over a large number of cases where flooding is forecast to occur with a probability of 0.95, it should be observed to occur roughly 95% of the time. However, the calculation of the observed relative frequency is subject to sampling uncertainty. For example, there may be few cases in the historic record where flooding is forecast to occur with probability 0.95. In practice, the forecasts are binned into discrete probability intervals and the observed relative frequencies are plotted against the average forecast probability within each bin. The sampling uncertainty will decline as the width of the bin increases, but the precision of the diagram will also decline.

The Reliability diagram plots the average forecast probability within each bin on the x-axis. For a forecast event defined by the non-exceedence of some threshold, t, the average probability of the forecasts that fall in the kth forecast bin, B_k is given by

$$\frac{1}{|I_k|}\sum_{i \in I_k} F_{Y_i}(t), \tag{A16}$$

where I_k denotes the set of all indices, $I_k = \{i : i \in B_k\}$, whose forecasts (and associated paired observations) fall in the kth bin and $|I_k|$ denotes the number of elements in that set. The y-axis shows the corresponding fraction of observations that fall in the kth bin

$$\frac{1}{|I_k|}\sum_{i \in I_k} \mathbf{1}\{t \geq x_i\}, \tag{A17}$$

where $\mathbf{1}\{t \geq x_i\}$ is a step function that assumes value 1 if the ith observation, x_i, exceeds the threshold, t, and 0 otherwise. If the forecast is perfectly reliable, the observed fraction within each bin will equal the average of the associated forecast probabilities, forming a diagonal line on the reliability diagram. Deviation from the diagonal line represents bias in the forecast probabilities, notwithstanding sampling uncertainty. The reliability diagram may be computed for several discrete events. Each event is represented by a separate reliability curve.

Collectively, the number of forecasts that fall within each of the k bins, $|I_k|$, denotes the 'sharpness' of the forecasts and is displayed as a histogram. Ideally, the forecast probabilities will be sharp, i.e. issued with little uncertainty, but also reliable.

Relative Operating Characteristic

The Relative Operating Characteristic (ROC; also known as the Receiver Operating Characteristic) measures the quality of a forecast for the occurrence of a discrete event, such as rainfall or flooding. For a probability forecast, the ROC curve measures the quality of a binary prediction or “decision” based on the forecast probability. A binary prediction is generated from the forecast by defining a probability threshold above which the discrete event is considered to occur. For example, a decision maker might issue a flood warning when the forecast probability of a flood exceeds 0.9. The ROC curve plots the forecast quality for several probability thresholds. Each threshold corresponds to a different level of risk aversion. For example, given a decision on whether to issue a flood warning, a probability threshold of 0.7 corresponds to a higher level of risk aversion (i.e. a lower threshold for warning) than a probability of 0.9. As the threshold declines, the probability of correctly detecting an event (the Probability of Detection or POD) will increase, but the probably of “crying wolf” (the probability of False Detection or POFD) will also increase. The ROC curve plots the trade-off between POD and POFD on two axes:

- Y-axis: the POD or probability with which an event is correctly forecast to occur. The POD is estimated from n sample data as the total number of correct forecasts divided by the total number of occurrences. For an event defined by the exceedance of a real-valued threshold, t, which is forecast to occur when the forecast probability exceeds a probability threshold, p_t, the POD is given by

$$\mathrm{POD}(t, p_t) = \frac{\sum_{i=1}^{n} \mathbf{1}\{1 - F_{Y_i}(t) > p_t \mid x_i > t\}}{\sum_{i=1}^{n} \mathbf{1}\{x_i > t\}}, \qquad \text{(A18)}$$

where $\mathbf{1}\{\cdot\}$ is a step function that assumes the value 1 if the condition, {·}, is met and 0 otherwise.

- X-axis: the POFD or probability with which an event is incorrectly forecast to not occur (i.e. the event occurs, but the forecast was for non-occurrence). The POFD is estimated from n sample data as the total number of incorrect forecasts divided by the total number of non-occurrences

$$\mathrm{POFD}(t, p_t) = \frac{\sum_{i=1}^{n} \mathbf{1}\{1 - F_{Y_i}(t) > p_t \mid x_i \le t\}}{\sum_{i=1}^{n} \mathbf{1}\{x_i \le t\}}. \qquad \text{(A19)}$$

These values are computed for probability thresholds that exhaust the unit interval, which is normally defined by a number of plotting points, q, that separate the unit interval, [0,1], into q thresholds at equal intervals. Additionally, the curve is forced to intersect (0,0), and (1,1).

For an ensemble forecasting system to perform well in terms of ROC, the POD must be high relative to the POFD. An ensemble forecasting system that produces forecasts in line with climatological expectation will have as many "successful" predictions as the climatological probability of the event implies. A skillful forecasting system will always produce a ROC curve that lies above the diagonal line.

Practical applications of the ROC in the medical, atmospheric, and other sciences frequently fit a smooth curve to the empirical POD and POFD data. A common approach is to fit a binormal model, which assumes that the POD and POFD are normally distributed, each with given mean and variance (standard deviation). Experience has shown that the binormal model typically provides a good fit to the empirical POD and POFD, even when they are "significantly" non-normal (i.e. the binormal approximation is robust). The binormal model is given by

$$\begin{aligned} &\mathrm{POD} = \Phi(a + b\Phi^{-1}(\mathrm{POFD})), \quad \text{where} \\ &a = \frac{\mu_{\mathrm{POD}} - \mu_{\mathrm{POFD}}}{\sigma_{\mathrm{POD}}}, \quad \text{and} \\ &b = \frac{\sigma_{\mathrm{POFD}}}{\sigma_{\mathrm{POD}}}. \end{aligned} \qquad \text{(A20)}$$

Here, Φ is the cumulative distribution function of the standard normal distribution, μ_{POD} and μ_{POFD} are, respectively, the means of the POD and POFD, and σ_{POD} and σ_{POFD} are their corresponding standard deviations.

There are several approaches to estimating the parameters of the binormal model, a and b (or the means and standard deviations from which they are derived; for example, see Cai and Moskowitz, 2004). The simplest and most direct approach stems from the observation that

$$\Phi^{-1}(\mathrm{POD}) = \mathrm{a} + \mathrm{b}\Phi^{-1}(\mathrm{POFD}). \tag{A21}$$

Hence, the parameters, a and b, are the intercept and slope, respectively, of a linear (regression) relationship between the POD and POFD *following* their transformation to the probit scale. The EVS estimates these parameters through ordinary least squares regression. While the resulting model fit is mathematically correct, the standard errors of the model (or confidence intervals for the associated ROC Score) cannot be computed in this way, and are not reported by the EVS. Since the parameters of the binormal model are estimated from the empirical POD and POFD, the model fit will depend on the number of probability thresholds used to compute the ROC curve. The number of thresholds cannot (usefully) exceed the number of ensemble members, m, (or m+1 thresholds) from which the POD and POFD are derived, as the ensemble forecast only contains information at these thresholds (members). However, the binormal curve is plotted for a large number of points in between these thresholds, in order to convey the smoothness of the fitted model.

The ROC Score is derived from the Area Under the Curve (AUC), and is an analytical function of the binormal model parameters

$$\mathrm{AUC} = \Phi\left(\frac{\mathrm{a}}{\sqrt{1+\mathrm{b}^2}}\right). \tag{A22}$$

Upon request, the binormal approximation to the ROC Score is also provided by the EVS. Since the model fit depends on the number of thresholds used to compute the ROC curve, the number of thresholds must be defined when computing the binormal approximation to the ROC Score. For an exact comparison between the binormal

ROC curve and the binormal ROC Score (or AUC), the same number of thresholds, q, must be used for each metric.

Relative Operating Characteristic Score

The Relative Operating Characteristic (also known as the Receiver Operating Characteristic) measures the quality of a forecast for the occurrence of a discrete event, such as rainfall or flooding. It does not consider the quality of forecasts that predict no occurrence of the event defined (e.g. no rainfall or no flooding).

The ROC Score is based on the area underneath the ROC curve or AUC, which is normalized by the AUC of a reference forecast, $\mathrm{AUC}_{\mathrm{ref}}$ (Mason and Graham, 2002). The AUC of the climatological probability forecast is 0.5, which corresponds to the diagonal line in the ROC plot. Thus, the ROC Score for the climatological probability forecast is

$$\mathrm{ROC\,Score} = \frac{\mathrm{AUC} - \mathrm{AUC}_{\mathrm{ref}}}{1.0 - \mathrm{AUC}_{\mathrm{ref}}} = \frac{\mathrm{AUC} - 0.5}{1.0 - 0.5} = 2 \times \mathrm{AUC} - 1. \qquad \text{(A23)}$$

As discussed under the Relative Operating Characteristic, practical applications of ROC analysis in the medical, atmospheric, and other sciences frequently fit a smooth curve to the paired values of the Probability of Detection (POD) and Probability of False Detection (POFD) derived from the sample data. A common approach is to fit a binormal model, which assumes that the POD and POFD are normally distributed, each with given mean and variance (standard deviation). Experience has shown that the binormal model typically provides a good fit to the empirical POD and POFD, even when the sample data are "significantly" non-normal (i.e. the binormal approximation is robust). The binormal approximation to the AUC (and hence the ROC Score) is given by

$$\mathrm{AUC} = \Phi\left(\frac{a}{\sqrt{1+b^2}}\right). \qquad \text{(A24)}$$

Here, a and b are the parameters of the binormal model, and Φ is the cumulative distribution function of the standard normal distribution. The parameters a and b are, respectively, the intercept and slope of the (assumed) linear relationship between the

POD and POFD *following* their transformation to the probit scale (see the discussion under the Relative Operating Characteristic). Unlike the empirical AUC (Mason and Graham, 2002), which bypasses the calculation of the ROC curve, the binormal approximation to the AUC (and ROC Score) is based on the q pairs of (POD, POFD) data from which the empirical ROC curve is computed (where q is the number of probability thresholds). Thus, for an exact comparison between the binormal ROC curve and the binormal ROC Score, the same number of thresholds, q, must be used for each metric. However, the binormal ROC Score will be closest to the empirical ROC Score when the ROC curve is constructed from m+1 probability thresholds, where m is the (fixed) number of ensemble members in each forecast. Put differently, the empirical AUC, described by Mason and Graham (2002), approximates the area under the ROC curve when constructed with as many probability thresholds as the (fixed) number of ensemble members in each forecast.

By default, the algorithm described in Mason and Graham (2002) is used to compute the empirical AUC. Optionally, the AUC may be derived from the empirical ROC curve, which is constructed for a specified number of points. In that case, the empirical ROC curve is integrated using the trapezoid rule. In most cases, the algorithm described by Mason and Graham (2002) generates larger values of the empirical AUC (skill) than integrating the empirical ROC curve.

Spread-bias diagram

For continuous random variables, such as temperature and streamflow, the SBD provides a simple measure of conditional reliability. It involves counting the fraction of observations, $\mathrm{SBD(I)}$, that fall within a probability interval of fixed width on the support of the ith forecast, $\mathrm{I} = [\mathrm{c}, \mathrm{d} \mid \mathrm{c}, \mathrm{d} \in [0,1]]$

$$\mathrm{SBD(I)} = \tfrac{1}{n}\sum_{i=1}^{n} \mathbf{1}\{\hat{F}_{m_i}(x_i^o) \in \mathrm{I}\}. \qquad \text{(A25)}$$

An ensemble forecasting system is reliable over the interval, I, if it captures observations in proportion to the width of that interval

$$\lim_{n,m\rightarrow\infty}\left\{\tfrac{1}{n}\sum_{i=1}^{n} \mathbf{1}\{\hat{F}_{m_i}(x_i^o) \in \mathrm{I}\}\right\} = \mathrm{d} - \mathrm{c}. \qquad \text{(A26)}$$

By defining k windows on the unit interval, $\left\{\mathrm{I}_{\mathrm{j}}=[\mathrm{c}_{\mathrm{j}},\mathrm{d}_{\mathrm{j}}]\,|\,\mathrm{c}_{\mathrm{j}},\mathrm{d}_{\mathrm{j}}\in[0,1];\mathrm{j}=1,...,\mathrm{k}\right\}$, the reliability can be determined for the entire range of forecast probabilities. In practice, the k windows may cover any subintervals of the unit interval. Certain windows may be preferred for some applications or for sampling reasons. For example, if the forecasts are uncertain in the tails, windows centered on the forecast median may be preferred. The SBD shows the observed frequency, $\mathrm{SBD(I)}$, against the expected frequency, $\mathrm{d\text{-}c}$. Any deviation from the diagonal line represents a lack of reliability in the forecast probabilities. More specifically, the ensemble forecasts are unreliable if the observed frequency, $\mathrm{SBD(I)}$, deviates from the expected frequency by more than the sampling uncertainty of $\mathrm{SBD(I)}$. If the k windows each cover a probability interval of $1/\mathrm{k}$, the expected frequency has a uniform probability distribution, and the actual reliability can be tested for its goodness-of-fit to a uniform distribution (e.g. using the one-sided Cramer von Mises test; Anderson, 1962; Elmore, 2005; Bröcker, 2008).

For continuous random variables, the expected $\mathrm{SBD(I)}$ is equal to the width of the interval, I, and is, therefore, strictly increasing as the width increases (see above). However, for mixed random variables, such as precipitation and wind-speed, the discrete portion of the probability distribution comprises an infinite number of intervals of different width. Although the window definition could be adapted for this case (see Hamill and Colucci, 1997 for a similar discussion), the reliability diagram may be preferred for mixed random variables.

While the SBD is analogous to the cumulative rank histogram, it explicitly defines the width of the interval, I, into which observations fall. When these windows are based on non-exceedence probabilities and are uniform in width (as well as non-overlapping and exhaustive), the SBD is also analogous to the Probability Integral Transform (PIT) (Casella and Berger, 1990), although the latter involves fitting a parametric cdf to the ensemble forecast distribution prior to evaluating the PIT (Gneiting et al., 2005). In that case, the SBD, the cumulative rank histogram and the PIT can also be summarized with the reliability component of the $\overline{\mathrm{CRPS}}$ (Hersbach, 2000), which tests whether an observation falls below a threshold with a frequency proportional to the cumulative probability of that threshold (averaged across all thresholds).

Rank histogram

The rank histogram measures the reliability of an ensemble forecasting system. It is similar to the spread-bias diagram and involves counting the fraction of observations that fall between any two ranked ensemble members in the forecast distribution (the spread-bias diagram uses an explicit probability interval derived from the members). For an ensemble forecast that comprises m ensemble members ranked in ascending order, there are $m+1$ “gaps”, $\{g_1,\ldots,g_{m+1}\}$, between any two ranked ensemble members (i.e. $m-1$ internal gaps, and one at each bound) into which the observation could fall. The rank histogram measures the fraction of observations, h, that fall within each gap

$$h_i = \frac{1}{n}\sum_{j=1}^{n}\mathbf{1}\{x_j \in g_{ij}\}. \qquad \text{(A27)}$$

where h_i is the fraction in the ith bin, x_j is the jth observed value, g_{ij} is the ith gap associated with the jth forecast, and $\mathbf{1}\{\cdot\}$ is a step function that assumes value 1 if the condition is met and 0 otherwise.

If the forecasting system is reliable in terms of the rank histogram, the probability that an observation falls between any two ranked ensemble members is approximately uniform. Indeed, the actual reliability can be tested for goodness-of-fit of the sample fractions to a uniform probability distribution (e.g. using the one-sided Cramer von Mises test; Anderson, 1962; Elmore, 2005; Broecker, 2008).

Notwithstanding any sampling and observational uncertainties (see below), a lack of uniformity in the rank histogram is indicative of an unreliable forecasting system. Greater than expected probabilities in the tails of the rank histogram (i.e. in low and high bins) can lead to a "U" shape, which is indicative of a lack of spread in the ensemble. Greater than expected probabilities in the center of the rank histogram (i.e. in central bins) can lead to an inverted "U" shape, which is indicative of too much spread in the ensemble. Other systematic features, such as a gradient, or a combination of features, may be indicative of biases in the mean and possibly higher moments of the ensemble.

While a perfectly reliable ensemble (in the context of the rank histogram) will ordinarily produce a rank histogram that is approximately uniform (given any sampling uncertainty), systematic non-uniformities are possible when the observations are uncertain, even if they are unbiased in the mean. The precise effects of observational uncertainty will depend upon the shapes of the two probability distributions (forecast and observed), but observational uncertainties typically exaggerate the probability of falling in the tails of the forecast distribution, falsely indicating a lack of spread in the ensemble or a "U-shaped" rank histogram (Hamill, 2001).

When computing the rank histogram, ties are handled by randomly assigning one of the tied ranks (i.e. assigning the observation randomly to one of the tied bins). In particular, this avoids the appearance of bias for mixed variables, such as precipitation; an artifact that stems from consistently assigning the observation to the lower (or higher) of the tied bins when the bins are, in fact, indistinguishable.

Mean error of probability diagram

The mean error of probability diagram (MEPD) measures the reliability of an ensemble forecasting system in an unconditional sense. Let z_{ij} denote the jth of m ensemble members from the ith of n ensemble forecasts and let x_i^o denote the observed outcome associated with the ith ensemble forecast. The forecast climatology has an empirical distribution function, $\hat{F}_{nm}(v)$, which is computed from the n ensemble forecasts as

$$\hat{F}_{nm}(v) = {}^{1}\!/\!_{n}\sum_{i=1}^{n}\hat{F}_{m_i}(v) \quad \text{where} \quad \hat{F}_{m_i}(v) = {}^{1}\!/\!_{m}\sum_{j=1}^{m}1\{z_{ij} \le v\}, \qquad \text{(A28)}$$

and $\mathbf{1}\{\cdot\}$ is a step function that assumes value 1 if the condition is met and 0 otherwise. Let $H = [a, b \mid a, b \in [0,1]]$ denote an interval of fixed width on the support of $\hat{F}_{nm}(v)$. The MEPD counts the fraction of observations that fall within the interval, H, namely

$$\text{MEPD(H)} = {}^{1}\!/\!_{n}\sum_{i=1}^{n}1\{\hat{F}_{nm}(x_i^o) \in H\}. \qquad \text{(A29)}$$

An ensemble forecasting system is unconditionally reliable or marginally calibrated over the interval, H, if it captures observations in proportion to the width of that interval

$$\lim_{n,m\to\infty}\left\{ 1/_{n}\sum_{i=1}^{n} 1\{\hat{F}_{nm}(x_i^o) \in H\} \right\} = b - a. \qquad \text{(A30)}$$

The MEPD shows $\mathrm{MEPD(H)}$ against the width of H for each of k windows that span the unit interval. In practice, the k windows may cover any subintervals of the unit interval. The MEPD is similar to the quantile-quantile (Q-Q) plot (Wilks, 2006) and the probability-probability (P-P) plot (Shorack and Wellner, 1986; Gneiting et al., 2007). The Q-Q plot compares the order statistics of two samples, or the order statistics of one sample against the values of a theoretical distribution at corresponding quantiles (Wilks, 2006). The P-P plot compares the quantiles corresponding to these order statistics. Indeed, the MEPD is equivalent to a P-P plot of the climatological distributions of X and Y when evaluated for the n intervals, $\left\{ H_j = [0, b_j] \mid b_j = j/_{n+1}, j = 1, ..., n \right\}$. As indicated above, the MEPD assumes asymptotic convergence of $\mathrm{MEPD(H)}$ as $n\to\infty$. In practice, this may be evaluated by comparing the $\mathrm{MEPD(H)}$ for g subsamples of the n available data.

APPENDIX A2 XML OUTPUT FORMATS

EVS produces three types of XML file, namely: 1) project files, which store previously defined VUs and AUs; 2) paired data files, which store the paired forecasts and observations associated with a single VU; and 3) product files containing the numerical results for particular verification metrics.

Project files

Project files store all of the parameters required to close and restart EVS without loss of information. A project file is produced or updated by clicking "**Save**" or "**Save as…**" at any point during the operation of EVS. The data are stored in XML format and are, therefore, human readable, and may be produced separately from EVS (e.g. for batch calculations in the future).

The XML contains the following tags, in hierarchical order:

Level 1 (top level):

```
<verification>  //Top level tag
<verification_unit> //Tag for a single verification unit (see Level 2)
<aggregation_unit> //Tag for a single aggregation unit (see Level 3)
```

Level 2 (verification unit, VU):

```
<verification_unit>
    <identifiers> //Identifiers for the VU (see Level 2a)
    <input_data> //Input data, including forecasts and observations (see Level 2b)
    <verification_window> //Verification window (see Level 2c)
    <output_data> //Output data options
        <output_data_location> //Output data location
        <output_graphics_format> //Output graphics format
    <paired_data> //Paired data file [only when defined] (see Level 2d)
    <metrics> //Verification metrics selected (see Level 2e)
```

Level 2a (VU identifiers):

```
<identifiers> //Identifiers for the VU
    <location_id> //Identifier for the forecast point
    <environmental_variable_id>  //Variable id (e.g. streamflow)
    <additional_id> // Additional id (e.g. forecast_model_1) [only when defined]
```

Level 2b (VU input data sources):

```
<input_data> //Identifiers for the VU
    <forecast_data_location> //Forecast data
        <file> //Path to first file/folder (e.g. first file in a file array or a folder)
        <file> //Path to second file in a file array [when defined]
        <file> //Etc.
         …
    <forecast_file_filter> //String for filtering files within a specified forecast directory
    <observed_data_location>  //Path to observed data file
    <observed_file_type>  //File type for observed data file
    <forecast_file_type>  //File type for forecast data file
    <forecast_file_variable_id>  //Variable name in forecast file [when defined]
    <observed_file_variable_id>  //Variable name in observed file [when defined]
    <forecast_time_system>  //Name of forecast time system
    <observed_time_system>  //Observed time system
    <forecast_support> //Scale of forecasts
        <statistic> //E.g. “instantaneous”
        <period> //E.g. “1” [only when defined: blank when statistic = instantaneous]
        <period_units> //E.g. “DAY” [when defined: as above]
        <existing_attribute_units> //E.g. “feet cubed/second”
        <target_attribute_units> //E.g. “meter cubed/second”
        <attribute_units_function> //Multiplier to arrive at stated attribute units [1.0]
        <notes>  //Additional textual info. [when defined]
    <observed_support> //Scale of observations [see forecast_support]
    <apply_date_cond_to_climatology> //Use date conditions for climate thresholds
    <apply_value_cond_to_climatology> //Use value conditions for climate thresholds
    <forecast_date_format>  //Date format for ASCII forecasts (e.g. MM/dd/yyyy HH)
    <observed_date_format>  //Date format for ASCII observations
    <global_null_value>  //Global no-data value
```

Level 2c (verification window for a given VU):

```
<verification_window> //Window parameters
    <start_date> //Start date (in UTC)
        <year> //Start year
        <month> //Start month of year
        <day> //Start day of month
    <end_date>  //End date, see start date
    <window_in_valid_time>  //Time system of verification window
    <first_lead_period>  //Minimum lead time considered
    <last_lead_period>  //Maximum lead time considered
    <forecast_lead_units>  //Units for the maximum lead time
    <aggregation_lead_period> //Temporal aggregation window [when defined]
    <aggregation_lead_units>  //Aggregation window units [when defined]
    <aggregation_lead_frequency> //Frequency of rolling aggregation [when defined]
    <aggregation_lead_frequency_units>  //Units of rolling aggregation [when defined]
    <aggregation_function>  //Function used to aggregate pairs [when defined]
    <sample_size_constraint>  //Constraint on minimum sample size per lead time
    <date_conditions>  //Date conditions (see Level 2c_1) [when defined]
    <value_conditions>  //Value conditions (see Level 2c_2) [when defined]
```

Level 2c_1 (date conditions on the verification window) [when defined]:

```
<date_conditions>  //Date conditions
    <valid_time>  //Date conditions based on forecast valid time
        <exclude_years> //Integer years to exclude from the overall range
        <exclude_months> //Integer months to exclude from the overall range
        <exclude_weeks> //Integer weeks to exclude from the overall range
        <exclude_days_of_week> //Integer days to exclude from the overall range
        <exclude_hours_of_day_UTC> //Integer [0,23] to exclude UTC hours of day
    <issue_time>  //Date conditions based on forecast issue time [see valid_time]
        …
```

Level 2c_2 (value conditions on the verification window) [only when defined]:

```
<value_conditions>  //Value conditions.
    <condition> //First of n possible conditions
        <unit_id> //Identifier of the VU on which the condition is built
        <forecast_type> //True for forecasts, false for observed values
        <statistic> //Name of statistic, e.g. mean
        <statistic_constant> //Constant associated with statistic [when defined]
        <consecutive_period> //Window size [when defined]
        <consecutive_period_units> //Window time units [when defined]
        <consecutive_period_statistic> //Window statistic [when defined]
        <logical_conditions> //Set of n possible logical arguments
                <function> //First logical argument
                        <name> //Unary function name, e.g. isLessThan (<)
                        <value>  //Unary function threshold, e.g. 0.5 means "< 0.5"
                …
    …
```

Level 2d (paired data for a given VU) [only when defined]:

```
<paired_data>  //Start of paired data specification
    <paired_data_location> //Path to paired data
    <eliminate_duplicates> //Is true to eliminate pairs with the same valid/lead times
    <write_conditional_pairs> //Is true to write the conditional pairs
    <write_unconditional_pairs> //Is true to write the unconditional pairs
    <write_gzip_pairs> //Is true to write pairs in a compressed gzip format
    <paired_write_precision> //Integer number of decimal places for writing pairs > 0
    <strip_nulls_from_paired_file> //Is true to not write null member values
    <raw_pairs_in_aggregated_res> //Store only aggregated pairs to save space
    <detection_limit>  //Detection limit (see Level 2d_1) [when defined]
    …
```

Level 2d_1 (detection limit):

```
<detection_limit >  //Set of n possible metrics to compute
    <limit> //The detection limit
    <bound> //The boundary to assign when falling outside the detection limit
    <type> //The logical test for the limit (isGreater, isLess, isGreaterEqual, isLessEqual)
…
```

Level 2e (verification metrics for a given VU):

```
<metrics>  //Set of n possible metrics to compute
    <metric> //First of n metrics
        <name> //Name of metric
        Storage of parameters follows: varies by metric
    …
```

Level 3 (aggregation unit, AU) [only when defined]:

```
<aggregation_unit>  //Aggregation unit
    <name> //The aggregation unit name
    <unit_id> //First of n possible VU identifiers associated with the aggregation unit
    …
    <weights> //Weights to assign to each of the n units identified above [sum to 1]
    <output_data > //See equivalent tag under VU
    <pool_pairs> //Is true to pool pairs from the VUs rather than average metrics
    <statistically_dependent> //Is true to sample VUs assuming perfect dependence
    <bootstrap> //Is true to compute bootstrap intervals for the AU if defined for the VUs
```

An example of an EVS project file is given below:

```
<?xml version="1.0" standalone="yes"?>
<verification>
<verification_unit>
        <identifiers>
                <location_id>HMOS</location_id>
                <environmental_variable_id>Streamflow</environmental_variable_id>
                <additional_id></additional_id>
        </identifiers>
        <input_data>
                <forecast_data_location>
                        <file>EVS_flow_ensemble_forecasts.fcst</file>
                </forecast_data_location>
                <forecast_file_filter>xml</forecast_file_filter>
                <observed_data_location>EVS_flow_observations.obs</observed_data_location>
                <forecast_file_type>ASCII</forecast_file_type>
                <observed_file_type>NWS-CARD</observed_file_type>
                <forecast_time_system>UTC - 12 hours</forecast_time_system>
                <observed_time_system>Coordinated Universal Time (UTC)</observed_time_system>
                <forecast_support>
                        <statistic>INSTANTANEOUS</statistic>
                        <existing_attribute_units>FEET CUBED/SECOND</existing_attribute_units>
                        <notes></notes>
                </forecast_support>
                <observed_support>
                        <statistic>INSTANTANEOUS</statistic>
                        <existing_attribute_units>FEET CUBED/SECOND</existing_attribute_units>
                        <notes></notes>
                </observed_support>
                <use_all_observations_for_climatology>false</use_all_observations_for_climatology>
                <apply_date_cond_to_climatology>false</apply_date_cond_to_climatology>
                <apply_value_cond_to_climatology>false</apply_value_cond_to_climatology>
                <forecast_date_format>MM/dd/yyyy HH</forecast_date_format>
                <observed_date_format>MM/dd/yyyy HH</observed_date_format>
                <global_null_value>-999.0</global_null_value>
        </input_data>
        <verification_window>
                <start_date>
                        <year>1997</year>
                        <month>0</month>
                        <day>1</day>
                </start_date>
                <end_date>
                        <year>2008</year>
                        <month>11</month>
                        <day>29</day>
                </end_date>
                <first_lead_period>0.0</first_lead_period>
                <last_lead_period>6.0</last_lead_period>
                <forecast_lead_units>DAY</forecast_lead_units>
                <sample_size_constraint>0.0</sample_size_constraint>
        </verification_window>
        <output_data>
                <output_data_location>output</output_data_location>
        </output_data>
        <paired_data>
                <paired_data_location>HMOS_Streamflow_pairs_raw.xml</paired_data_location>
                <eliminate_duplicates>true</eliminate_duplicates>
                <write_conditional_pairs>true</write_conditional_pairs>
                <write_unconditional_pairs>true</write_unconditional_pairs>
                <write_gzip_pairs>true</write_gzip_pairs>
                <paired_write_precision>5</paired_write_precision>
                <strip_nulls_from_paired_file>true</strip_nulls_from_paired_file>
                <raw_pairs_in_aggregated_res>false</raw_pairs_in_aggregated_res>
                <detection_limit>
                        <limit>0.01</limit>
                        <bound>0.0</bound>
                        <type>isLess</type>
                </detection_limit>
        </paired_data>
        <metrics>
                <metric>
                        <name>BrierScore</name>
                        <probability_array_parameter>-Infinity,0.75,0.9</probability_array_parameter>
                        <main_threshold>true, true, true</main_threshold>
                        <threshold_condition>isGreater</threshold_condition>
                        <decompose_parameter>NONE</decompose_parameter>
                        <forecast_type_parameter>regular</forecast_type_parameter>
                        <unconditional_parameter>false</unconditional_parameter>
                        <minimum_sample_size_parameter>1</minimum_sample_size_parameter>
                        <bootstrap_parameters>
                                <technique>None</technique>
                        </bootstrap_parameters>
                </metric>
                <metric>
                        <name>Correlation</name>
                        <probability_array_parameter>-Infinity,0.75,0.9</probability_array_parameter>
                        <main_threshold>true, true, true</main_threshold>
                        <threshold_condition>isGreater</threshold_condition>
                        <forecast_type_parameter>regular</forecast_type_parameter>
                        <unconditional_parameter>false</unconditional_parameter>
                        <vector_function_parameter>Mean</vector_function_parameter>
                        <minimum_sample_size_parameter>1</minimum_sample_size_parameter>
                        <bootstrap_parameters>
                                <technique>None</technique>
                        </bootstrap_parameters>
                </metric>
                <metric>
                        <name>MeanContRankProbScore</name>
```

```
                    <probability_array_parameter>-Infinity,0.75,0.9</probability_array_parameter>
                    <main_threshold>true, true, true</main_threshold>
                    <threshold_condition>isGreater</threshold_condition>
                    <decompose_parameter>CR</decompose_parameter>
                    <forecast_type_parameter>regular</forecast_type_parameter>
                    <unconditional_parameter>false</unconditional_parameter>
                    <minimum_sample_size_parameter>1</minimum_sample_size_parameter>
                    <bootstrap_parameters>
                              <technique>None</technique>
                    </bootstrap_parameters>
                    <crps_method>hersbach</crps_method>
          </metric>
          <metric>
                    <name>SampleSize</name>
                    <probability_array_parameter>-Infinity,0.75,0.9</probability_array_parameter>
                    <main_threshold>true, true, true</main_threshold>
                    <threshold_condition>isGreater</threshold_condition>
                    <forecast_type_parameter>regular</forecast_type_parameter>
                    <unconditional_parameter>false</unconditional_parameter>
          </metric>
     </metrics>
</verification_unit>
</verification>
```

Advanced options only available in the EVS project file:

Occasionally, in testing experimental or advanced options, these options are only accessible via the EVS project file. The current experimental options are summarized below with an XML code block provided for context. These options should be used with care.

Tag: `<minimum_sample_size_parameter>`

Function: Sets a minimum sample size constraint on computing a given metric. If the constraint is not met, the metric will not be computed. The precise meaning of that constraint varies between metrics. For example, when computing dichotomous metrics (i.e. metrics computed with respect to discrete events), such as the Brier Score or reliability diagram, the minimum sample size refers to the smaller of the number of occurrences and non-occurrences of the event. For continuous metrics, such as the mean error or the CRPS, it simply comprises the number of samples from which the metric was computed.

Context:

```
<metric>
```

```
    <name>BrierScore</name>
    <probability_array_parameter>0.0,0.025 </probability_array_parameter>
    <main_threshold>true, false</main_threshold>
    <threshold_condition>isGreater</threshold_condition>
    <decompose_parameter>CR_LBR</decompose_parameter>
    <forecast_type_parameter>regular</forecast_type_parameter>
    <unconditional_parameter>false</unconditional_parameter>
    <minimum_sample_size_parameter>30</minimum_sample_size_parameter>
    <bootstrap_parameters>
        <technique>None</technique>
    </bootstrap_parameters>
</metric>
```

Tag: `<thinning>`

Function: Verification results are sensitive to the paired forecasts and observations available. Forecasts and observations from consecutive lead times and from adjacent locations are typically related to each other or “statistically dependent”. If the verification pairs contain shared information, the effective sample size is smaller than the nominal sample size. Particularly when the nominal sample size is small (e.g. extreme events), the verification results may be over-sensitive to a small number of observed events that are shared across multiple forecast issue times. In order to explore these sensitivities, the verification pairs may be thinned using a prescribed start index and interval. Only those forecasts issued at the start index and every subsequent nth index will be retained for verification.

Context:

```
<verification_window>
    <start_date>
        <year>1985</year>
        <month>0</month>
        <day>1</day>
    </start_date>
    <end_date>
        <year>2008</year>
        <month>11</month>
        <day>31</day>
    </end_date>
    <window_in_valid_time>false</window_in_valid_time>
    <first_lead_period>24.0</first_lead_period>
    <last_lead_period>360.0</last_lead_period>
    <forecast_lead_units>HOUR</forecast_lead_units>
    <aggregation_lead_period>1</aggregation_lead_period>
    <aggregation_lead_units>DAY</aggregation_lead_units>
    <aggregation_function>MEAN</aggregation_function>
```

```
                <sample_size_constraint>0.1</sample_size_constraint>
                <thinning>
                        <start_index>0</start_index>
                        <frequency>3</frequency>
                </thinning>
        </verification_window>
```

Tag: `<metric>`

Function: The Ensemble Quantile-Quantile Diagram is used to measure the unbiasedness of the (average) climatology of the ensemble members. The metric forms an average of the order statistics of the individual ensemble members and compares them to the corresponding order statistics of the observations.

Context:

```
<metrics>
        <metric>
                <name>EnsembleQQDiagram</name>
                <forecast_type_parameter>regular</forecast_type_parameter>
                <unconditional_parameter>false</unconditional_parameter>
                <bootstrap_parameters>
                        <technique>None</technique>
                </bootstrap_parameters>
        </metric>
<metrics>
```

Paired data files

A paired data file stores the pairs of forecasts and observations for a single VU in XML format. The file name corresponds to the VU identifier with a `_pairs.xml` extension.

Each pair comprises one or more forecasts and one observation, and is stored under a `<pr>` tag. Each pair has a readable date in Coordinated Universal Time (UTC or GMT), a lead time in hours (`<ld_h>`), an observation (`<ob>`), one or more forecast values (`<fc>`), and an internal time in hours (`<in_h>`) used by EVS to read the pairs (in preference to the UTC date). The internal time is incremented in hours from the forecast start time (represented in internal hours) to the end of the forecast time horizon. When multiple forecasts are present, each forecast represents an ensemble member, and each ensemble member is listed in trace-order, from the first trace to the last. An example of the first few lines of a pair within a paired file is given below:

```
<pairs>  //Denotes start of paired data
<pair_count>448<pair_count>    //Total number of pairs on file
<pr>    //First pair
      <dt>  //Date tag
            <y>2005</y>  //Year
            <m>11</m>  //Month
            <d>31</d>  //Day
            <h>18</h>  //Hour
      </dt>  //End of date tag
      <ld_h>6.0</ld_h>  //Lead time in hours
      <ob>150.625</ob>  //Observed value
      <fc>  //Forecast values: in this case 49 ensemble members
            157.31567,157.31598,157.31627,157.3342,157.3148,
            157.31598,157.31509,157.31509,157.31572,157.31567,
            157.31538,157.31598,157.31598,157.3148,157.31627,
            157.31393,157.31567,157.31598,157.31595,
            157.31627,157.32852,157.31569,157.3148,157.34517,
            157.34586,157.34148,157.31664,157.31538,
            157.31509,157.31644,157.31509,157.31567,
            157.31639,157.31598,157.31598,157.31627,
            157.31598,157.31567,157.3161,157.31538,157.34439,
            157.3148,157.31627,157.3148,157.31598,157.31598,
            157.31657,157.3156,157.31567
      </fc>
      <in_h>315570</in_h>  //Internal hour incremented from start time
</pr>    //End of first pair tag
…
…

</pairs>  //Denotes end of paired data
```

Product files

Product files include the numerical and graphical results associated with verification metrics.

Numerical results are written in XML format. One file is written for each metric. The file name comprises the unique identifier of the VU or AU, together with the metric name (e.g. `CBNK1.Q.Mean_error.xml`). Some metrics, such as reliability diagrams, have results for specific thresholds (e.g. probability thresholds). In that case, the results are stored by lead time and then by threshold value. The actual data associated with a result always appears within a 'values' tag. A metric result that comprises a single value will appear as a single value in this tag. A metric result that comprises a 1D matrix will appear as a row of values separated by commas in the input order. A metric result that comprises a 2D matrix will appear as a sequence of rows, each with a <values> tag, which are written in the input order. For example, a diagram metric with an x and y axis will comprise two rows of data (i.e. two rows within two separate <values> tags). The default input order would be data for the x axis followed by data for the y axis. Data that refer to cumulative probabilities are, by default, always defined in increasing size of probability. If available, sample counts are given in the last <values> tag. Sample counts are also printed out in a separate XML file for each metric. This information is written to a file with the VU identifier, metric name and a `_metadata.xml` extension.

An example of the first few lines of a numerical result file for one metric, namely the ‘mean error, is given below:

```
<results>      //Denotes the start of the results data
<meta_data>    //Tag for metadata on the results
           //The next tag indicates whether the results are ordered by one or more
           thresholds of the observed variable as well as by forecast lead time
           <thresholds_type>true</thresholds_type>
           <original_file_id>CBNK1.Q.mean_error.xml</original_f
           ile_id > //Original file name
</meta_data>  //End of metadata
<result>  //First of n possible results
      <lead_hour>6</lead_hour>    //Result applies to lead hour 6
      <threshold_data>
           <threshold>
                 //Threshold value > 5.0
                 <threshold_value>GT 5.0</threshold_value>
                 <data>  //Start of data
                      <values>0.0</values>  //Mean error
                 </data>  //End of data
           </threshold>
           …

      </threshold_data>  //End of data
</result>  //End of first result
…
…

</results>     //Denotes the end of the results data
```

For verification measures that comprise multiple factors alongside the overall scores, these factors are written as comma delimited values in a <values> tag. The order of the factors is described in Table A2a.

Table A2a: order of the score components written to file for score decompositions

Score	Decomposition	Elements	Order of elements (red = research use)
CRPS	None	1	CRPS
	Calibration-refinement (CR)	5	CRPS, reliability, resolution, uncertainty, potential CRPS
CRPSS	None	1	CRPSS
	CR	5	CRPSS, relative reliability, relative resolution, relative uncertainty, potential skill
BS	None	1	BS
	CR	4 (9)	BS, reliability, resolution, uncertainty, BS (event occurred), BS (event not occurred), sample count, sample count (event occurred), sample count (event not occurred)
	Likelihood-base-rate (LBR)	4 (11)	BS, Type-II conditional bias, discrimination, sharpness, Type-II CB (event occurred), Type-II CB (event not occurred), discrimination (event occurred), discrimination (event not occurred), sample count, sample count (event occurred), sample count (event not occurred)
	CR and LBR	7 (13)	BS, reliability, resolution, uncertainty, Type-II conditional bias, discrimination, sharpness, BS (event occurred), BS (event not occurred), Type-II CB (event occurred), Type-II CB (event not occurred), discrimination (event occurred), discrimination (event not occurred)
BSS	None	1	BSS
	CR	4	BSS, relative reliability, relative resolution, relative uncertainty
	LBR	4	BSS, relative Type-II conditional bias, relative discrimination, relative sharpness
	CR and LBR	7 (18)	BSS, relative reliability, relative resolution, relative uncertainty, relative Type-II conditional bias, relative discrimination, relative sharpness, BSS (event occurred), BSS (event not ocurred), Type II conditional bias (event occurred), Type II conditional bias (event not occurred), relative discrimination (event occurred), relative discrimination (event not occurred), relative reliability skill score, relative resolution skill score, relative Type-II conditional bias skill score, relative discrimination skill score, relative sharpness skill score

Reformatting product files: an example of an XSLT transformation

In order to read the EVS outputs into a secondary application, it may be necessary to change the data format. The Extensible Stylesheet Language Transformation (XSLT) applies a transform to an XML document, allowing the data to be filtered, manipulated or transformed into another format, such as ASCII CSV or html. The transform is specified in a stylesheet. A description can be found here:

http://en.wikipedia.org/wiki/XSLT

The ability to manipulate or transform the XML outputs from the EVS into another format is implemented on the command line as follows:

```
java -jar EVS.jar -xslt input.xml style.xml output
```

where:

- `xslt` is the command to perform the transform
- `input.xml` is the input xml file containing the EVS xml output data
- `style.xml` is the XSLT style sheet in which the transform is specified
- `output` is the output location, such as a text file [an empty argument will print to standard out]

As indicated above, the transform is specified in the XSLT stylesheet, `style.xml`. This can be modified to extract any information required from the EVS output files and then re-directed to any output stream as necessary. For example, the correlation coefficient may be extracted from an EVS output file in XML format and written to another file in CSV format. In order to process the correlation coefficient at each forecast lead time and for the main threshold only ("All data"), the XSLT stylesheet may comprise (omitting the commentary in an actual application):

```
<xsl:stylesheet version="1.0" xmlns:xsl="http://www.w3.org/1999/XSL/Transform">
<xsl:output method="text" indent ="no"/> Write output in text format without indenting
```

```
<xsl:template match="/">
       <xsl:text>Lead time, correlation&#xa;</xsl:text> Titles and line separator
       <xsl:for-each select="results/result"> Iterate through all result blocks
Print lead hour       <xsl:value-of       select="lead_hour"/>,       <xsl:for-each
select="threshold_data/threshold"> Iterate through each threshold
                      <xsl:if test="threshold_value = 'All data'"> If = All data:
                             <xsl:value-of select="data/values"/> select values
                             <xsl:text>&#xa;</xsl:text> Add new line
                      </xsl:if>
               </xsl:for-each>
       </xsl:for-each>
</xsl:template>
</xsl:stylesheet>
```

Subject to defining appropriate XSLT stylesheets, the EVS outputs are easily reformatted for secondary applications, such as displaying verification results on a website.

APPENDIX A3 REFERENCES

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